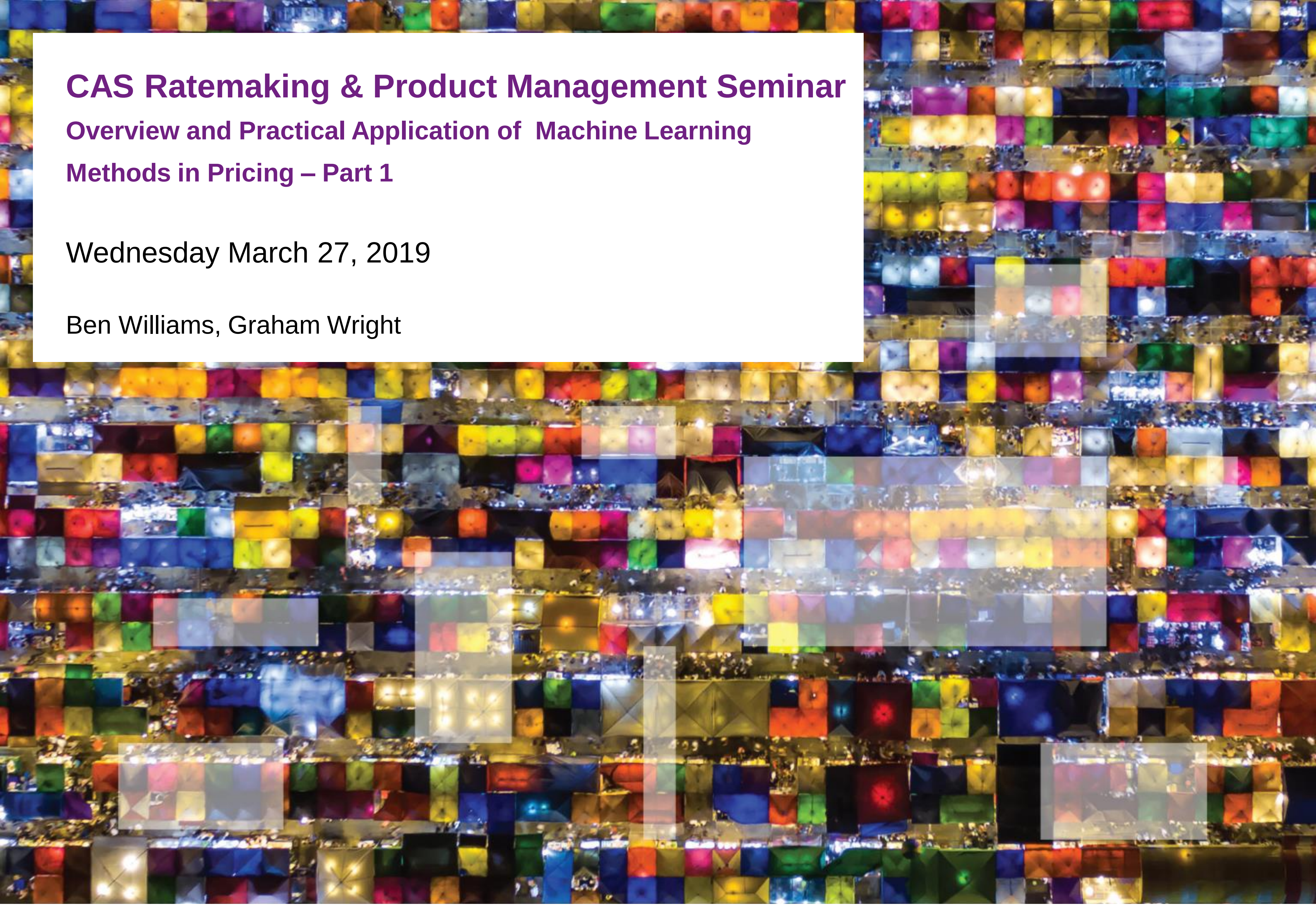


CAS Ratemaking & Product Management Seminar

Overview and Practical Application of Machine Learning Methods in Pricing – Part 1

Wednesday March 27, 2019

Ben Williams, Graham Wright

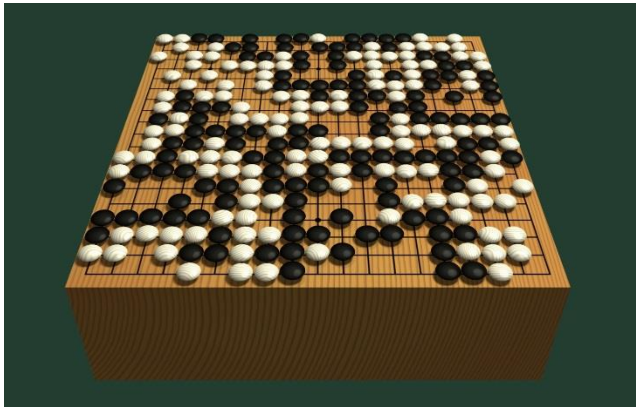
Willis Towers Watson

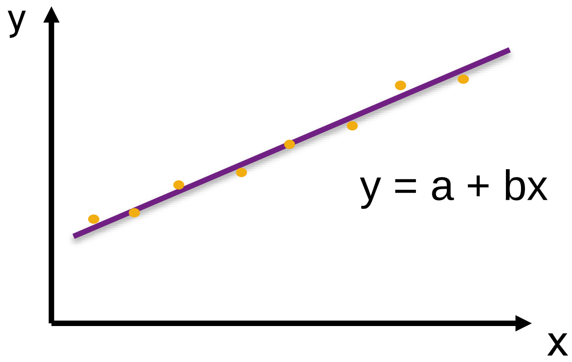
Agenda

Agenda
Context of machine learning in pricing
Session 1:
Decision trees **Random forests** **Gradient boosting machines**
Session 2:
“Earth” **Penalized regression** **Neural networks**
Conclusions
Q&A

Objective: to give you a working knowledge of some machine learning methods that may be used to improve GLM results and/or offer valuable insights in their own right in the field of P&C insurance pricing

Who’s interested in what?



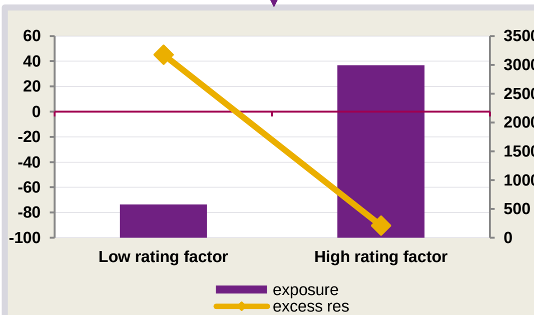


Applications of machine learning in the insurance sector

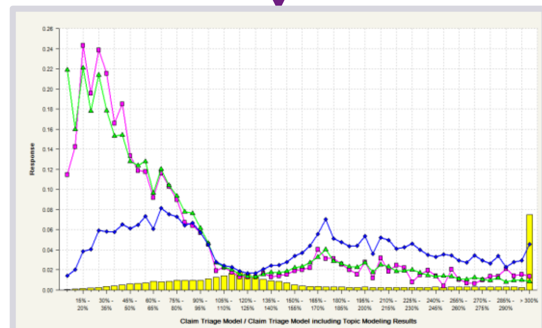
Marketing and Distribution → Customer management → Underwriting and risk management → Pricing → Claims management → Asset management

- Product development (UBI)
- Retention segmentation and program design
- Agent/Broker performance evaluation
- Fraud detection

P&C to Life cross-selling

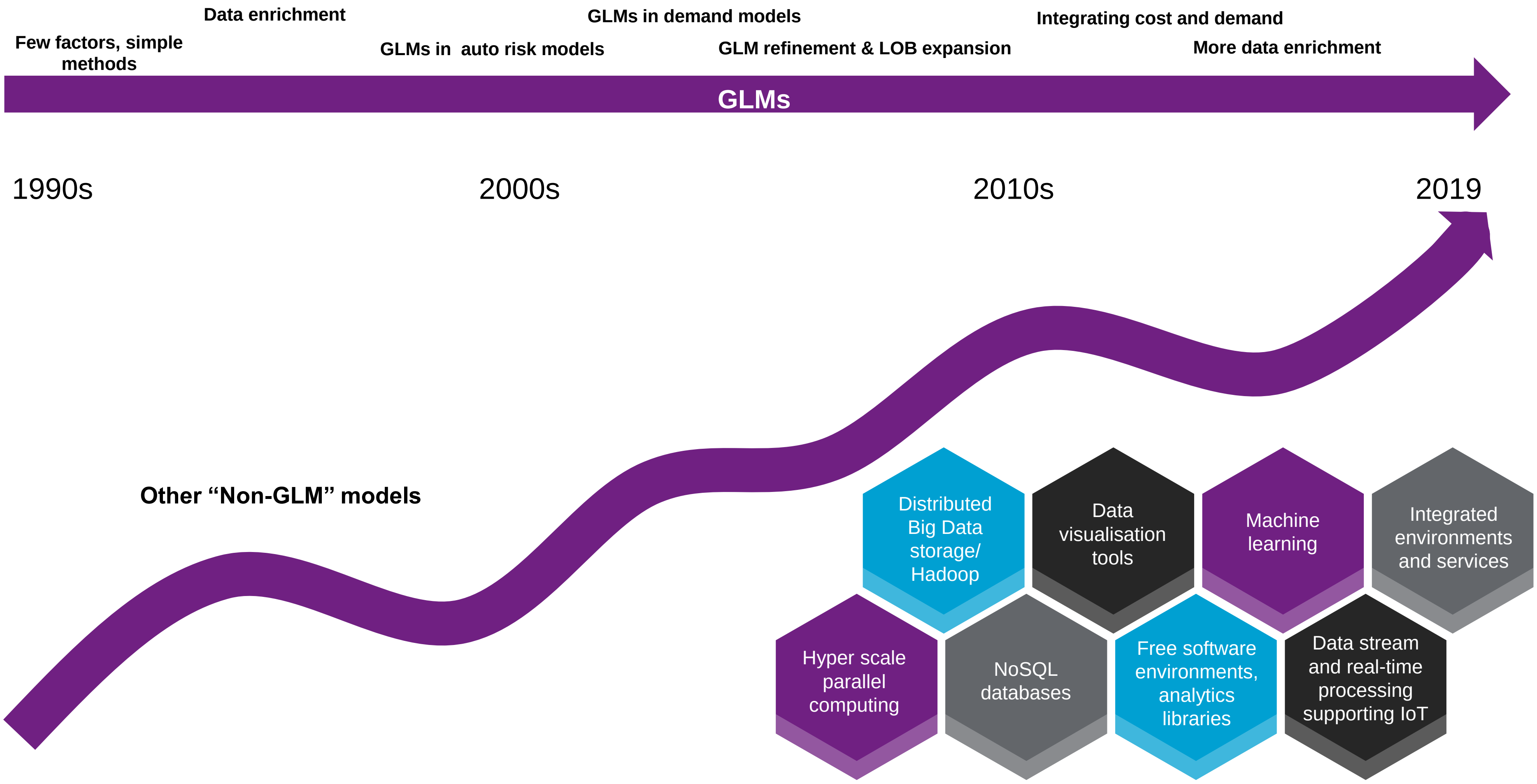


Web-scraping and feature design in commercial lines



Topic modeling and large loss modeling

This is not new….



What are these machine learning methods?

Ensembles

Classifications Trees

"Earth"

Regression Trees

Gradient Boosting Machines

K-nearest Neighbors

Elastic Net

Neural Networks

Naïve Bayes

Random Forests

K-Means Clustering

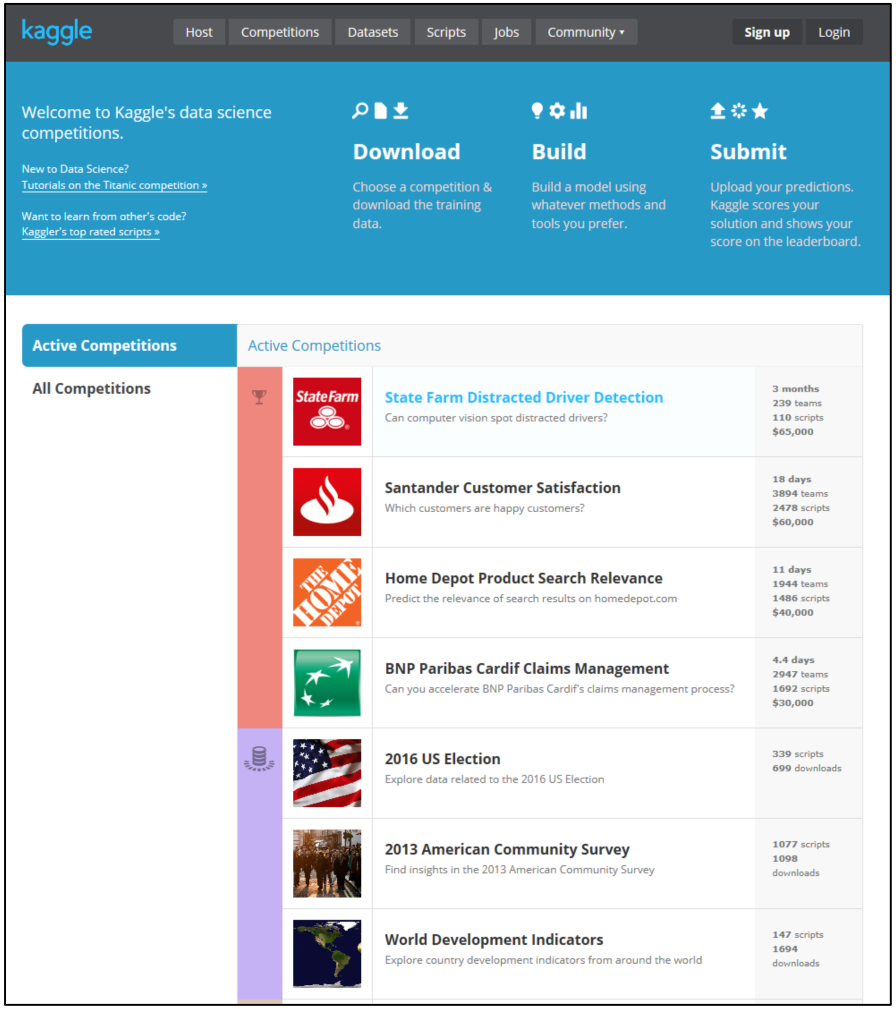
Principal Components Analysis

Lasso

Support Vector Machines

Ridge Regression

Kaggle



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Choose a competition & download the training data.
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Build a model using whatever methods and tools you prefer.
Submit
Upload your predictions. Kaggle scores your solution and shows your score on the leaderboard.
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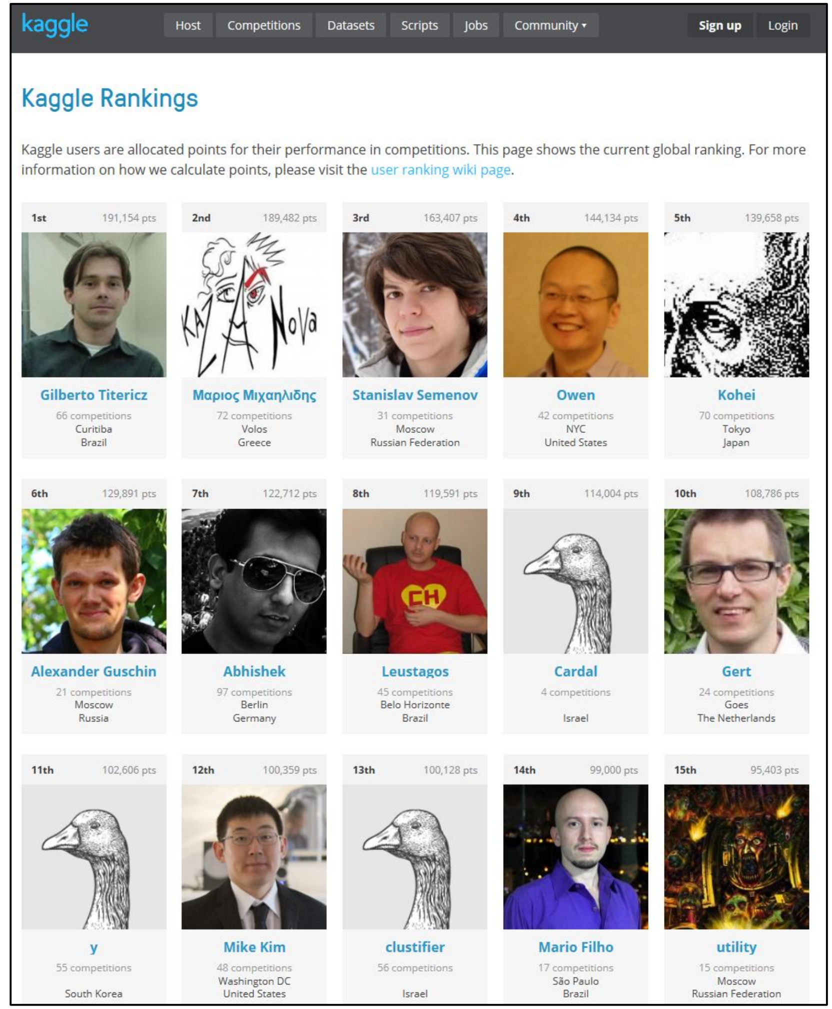
All Competitions
Active Competitions
State Farm
State Farm Distracted Driver Detection
Can computer vision spot distracted drivers?
3 months
239 teams
110 scripts
$65,000
Santander Customer Satisfaction
Which customers are happy customers?
18 days
3894 teams
2478 scripts
$60,000
Home Depot Product Search Relevance
Predict the relevance of search results on homedepot.com
11 days
1944 teams
1486 scripts
$40,000
BNP Paribas Cardif Claims Management
Can you accelerate BNP Paribas Cardif's claims management process?
4.4 days
2947 teams
1692 scripts
$30,000
2016 US Election
Explore data related to the 2016 US Election
339 scripts
699 downloads
2013 American Community Survey
Find insights in the 2013 American Community Survey
1077 scripts
1098 downloads
World Development Indicators
Explore country development indicators from around the world
147 scripts
1694 downloads



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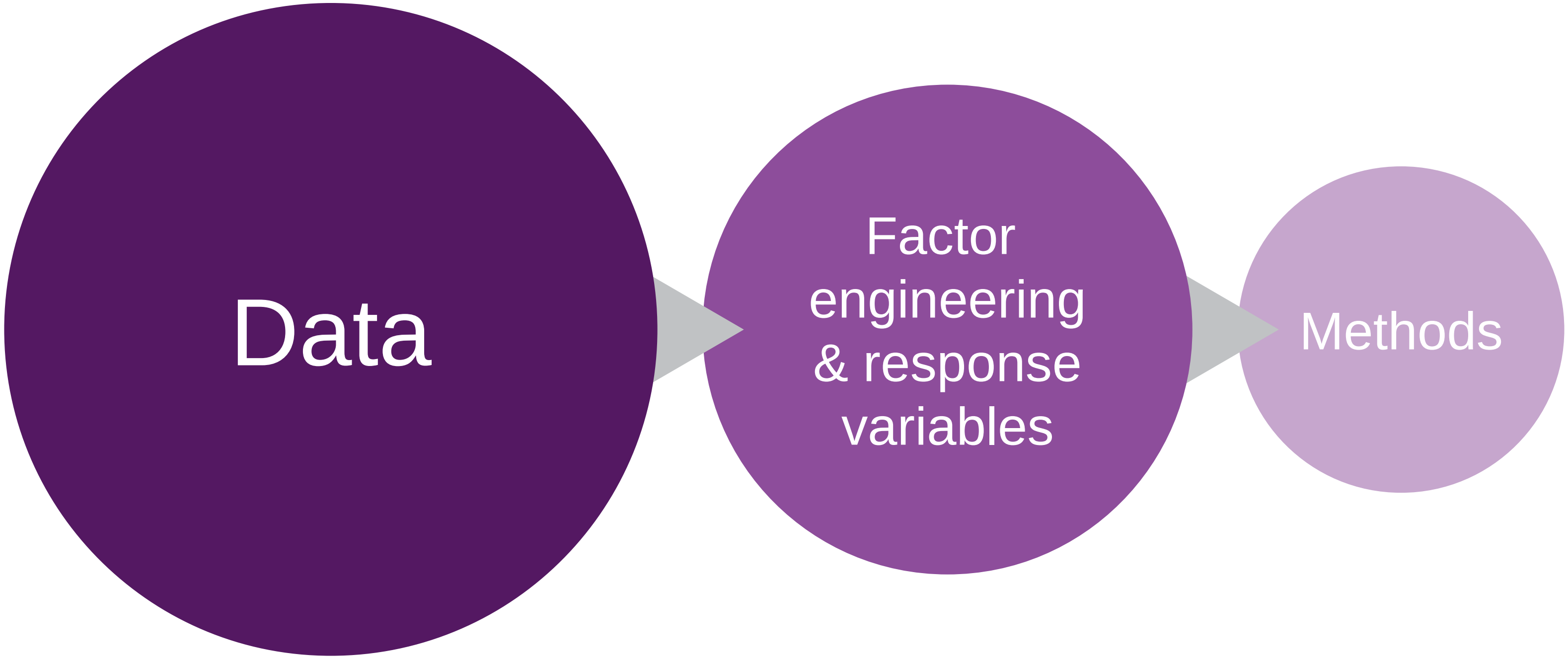
Gilberto Titericz
66 competitions
Curitiba
Brazil
2nd 189,482 pts
Μαριος Μιχαηλιδης
72 competitions
Volos
Greece
3rd 163,407 pts
Stanislav Semenov
31 competitions
Moscow
Russian Federation
4th 144,134 pts
Owen
42 competitions
NYC
United States
5th 139,658 pts
Kohei
70 competitions
Tokyo
Japan
6th 129,891 pts
Alexander Guschin
21 competitions
Moscow
Russia
7th 122,712 pts
Abhishek
97 competitions
Berlin
Germany
8th 119,591 pts
Leustagos
45 competitions
Belo Horizonte
Brazil
9th 114,004 pts
Cardal
4 competitions
Israel
10th 108,786 pts
Gert
24 competitions
Goes
The Netherlands
11th 102,606 pts
y
55 competitions
South Korea
12th 100,359 pts
Mike Kim
48 competitions
Washington DC
United States
13th 100,128 pts
clustifier
56 competitions
Israel
14th 99,000 pts
Mario Filho
17 competitions
São Paulo
Brazil
15th 95,403 pts
utility
15 competitions
Moscow
Russian Federation

Is it really all about the method?



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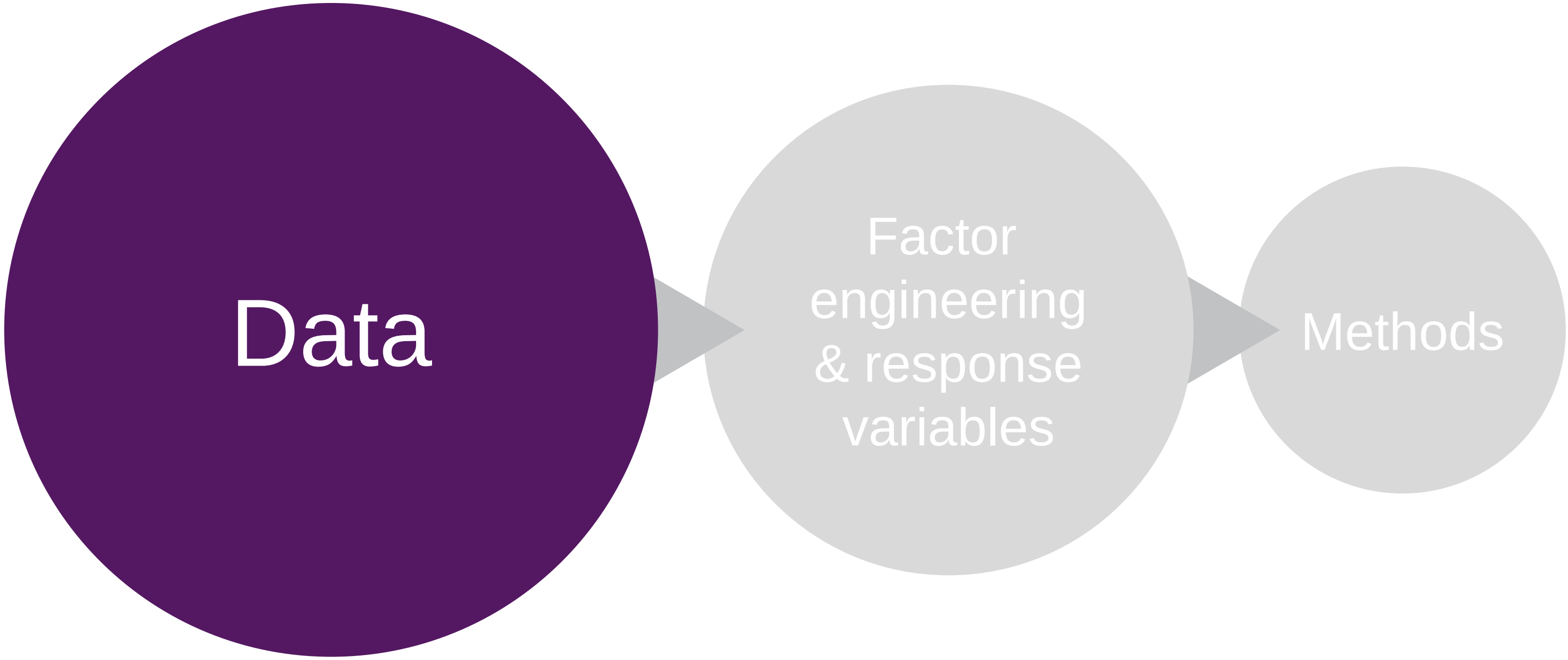

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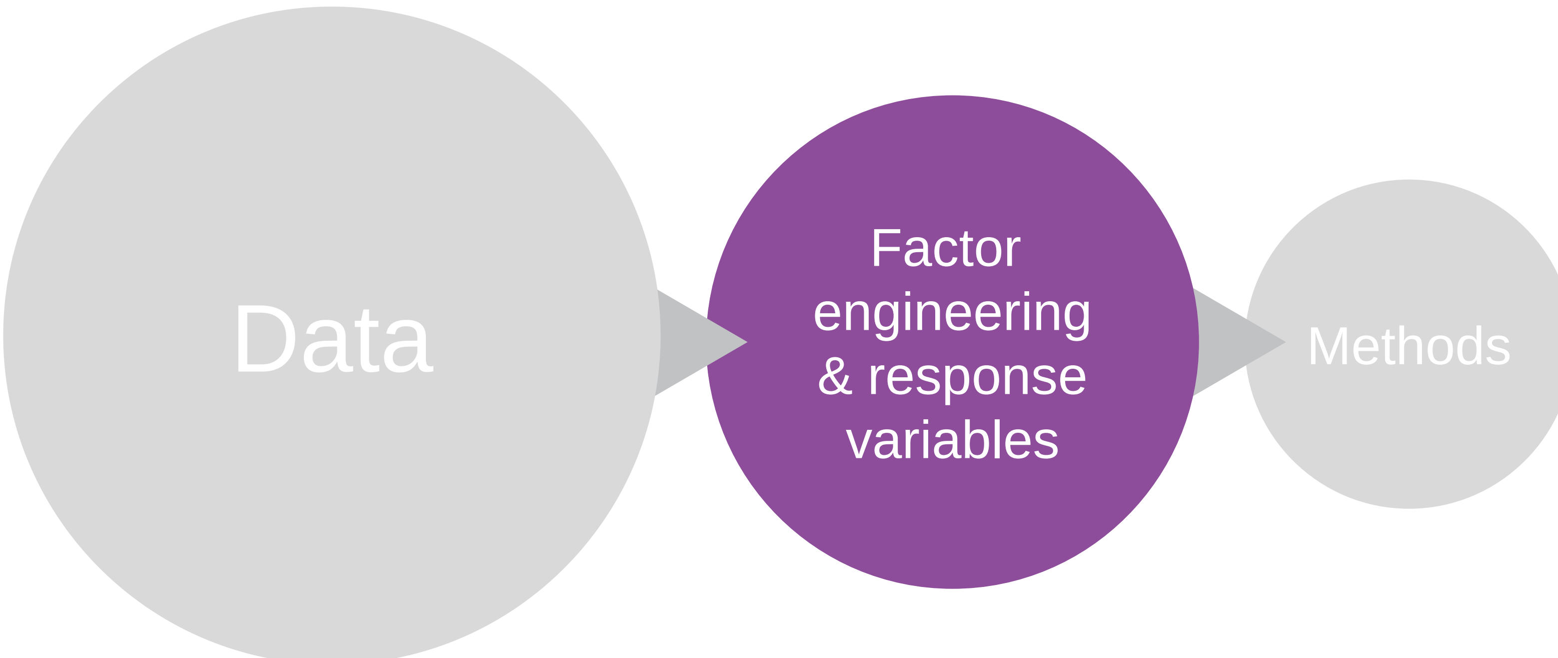

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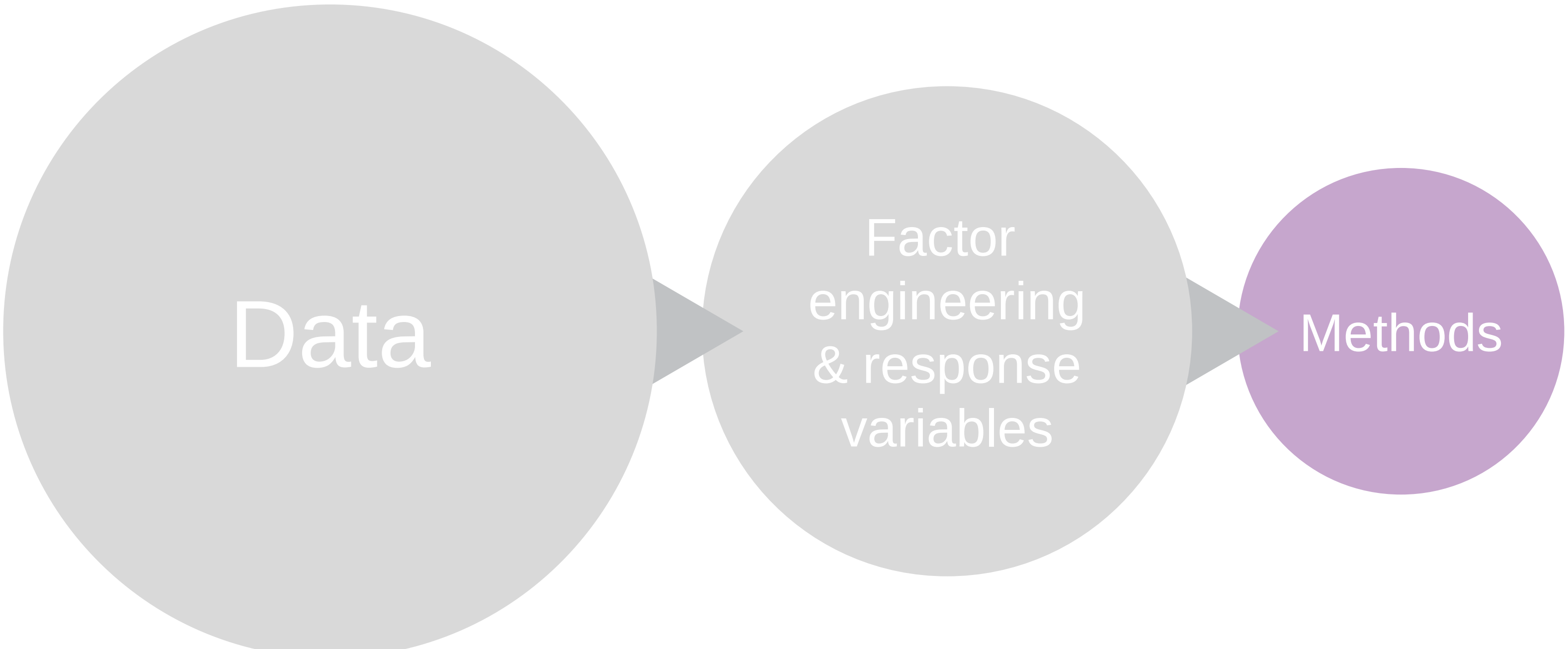
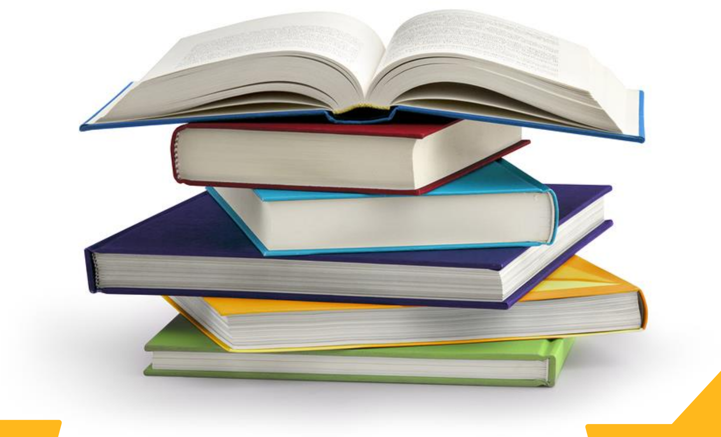


How do you know if a method works?

AIC

Gini

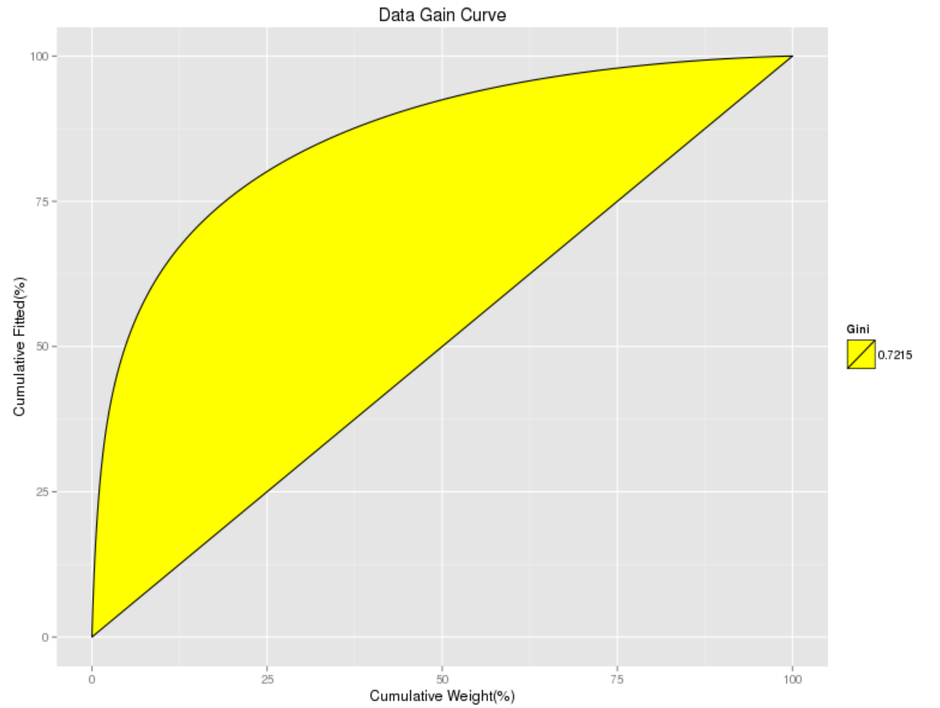
RMSE



MAE

Log
loss

How do you measure value?



- Rank hold out observations by their **fitted values** (high to low)
- **Plot cumulative response** by cumulative exposure
- A **better model** will explain a **higher proportion of the response** with a **lower proportion of exposure**
- …and will give a **higher Gini coefficient** (yellow area)

Example results

Model	Gini
GLM	0.327

Example results

Model	Gini
GLM	0.327
New Model	0.330

Example results

Model	Gini	Gini improvement
GLM	0.327	0.0%
New Model	0.330	1.0%

Example results

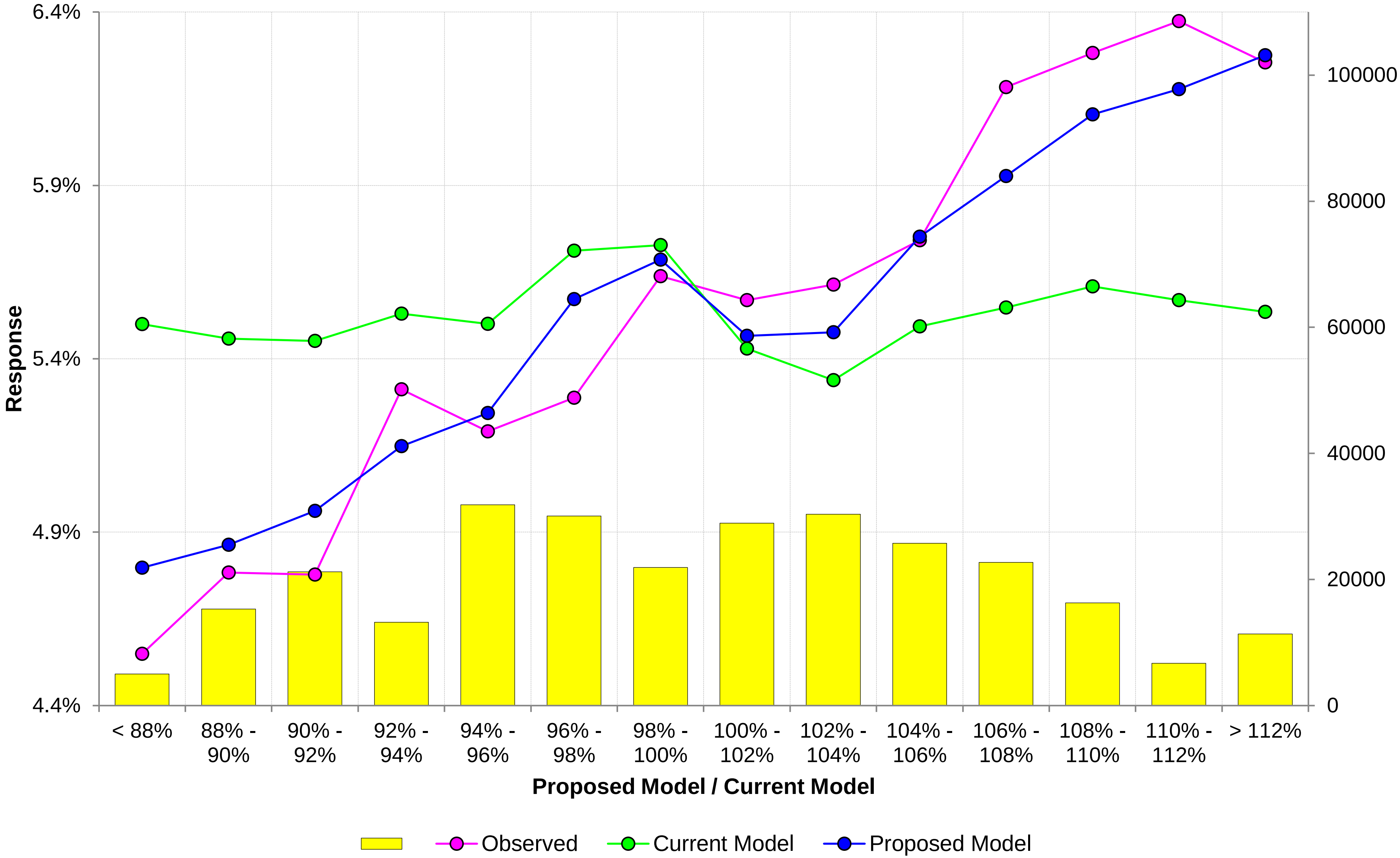
Model	Gini	Gini improvement	Gini rank
GLM (main factor removed)	0.318	-2.6%	4
GLM (minor factor removed)	0.322	-1.3%	3
GLM	0.327	0.0%	2
New Model	0.330	1.0%	1

But…

- Think of a model…
- Multiply it by 123
- Square it
- Add 74½ billion

- …and you get the same Gini coefficient!

Double lift chart



Financial value estimate

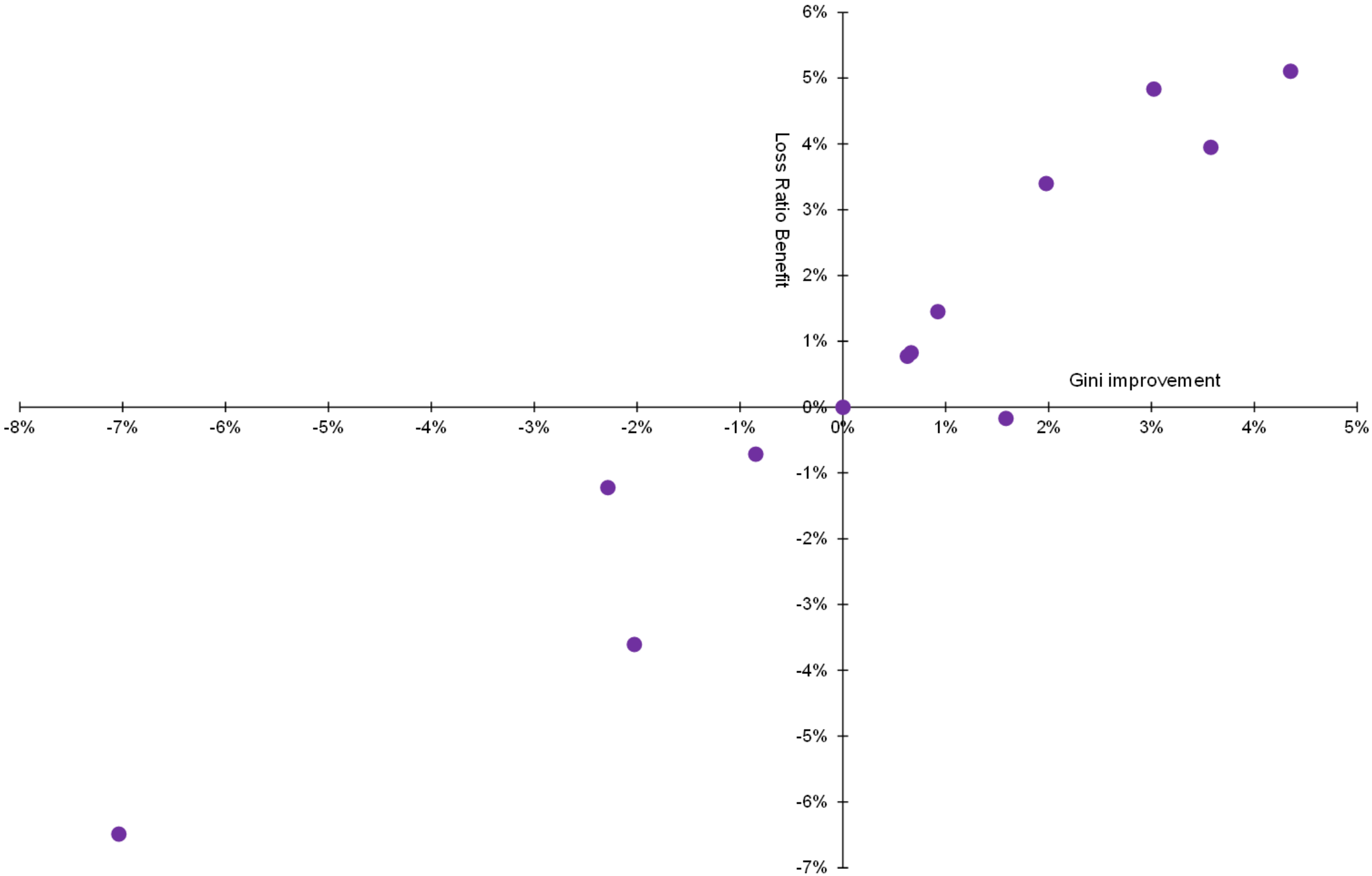
- Errors in insurance pricing are not symmetrical
- Financial benefit can be estimated

Example results redacted from printed version

Example results

Model	Gini	Gini improvement	Gini rank	Loss ratio @ elasticity 6	Loss ratio rank	Loss ratio @ elasticity 2	Loss ratio rank
GLM (main factor removed)	0.318	-2.6%	4	-0.9%	4	-0.4%	4
GLM (minor factor removed)	0.322	-1.3%	3	-0.4%	3	-0.2%	3
GLM	0.327	0.0%	2	0.0%	2	0.0%	2
New Model	0.330	1.0%	1	2.2%	1	0.5%	1

Financial value vs Gini

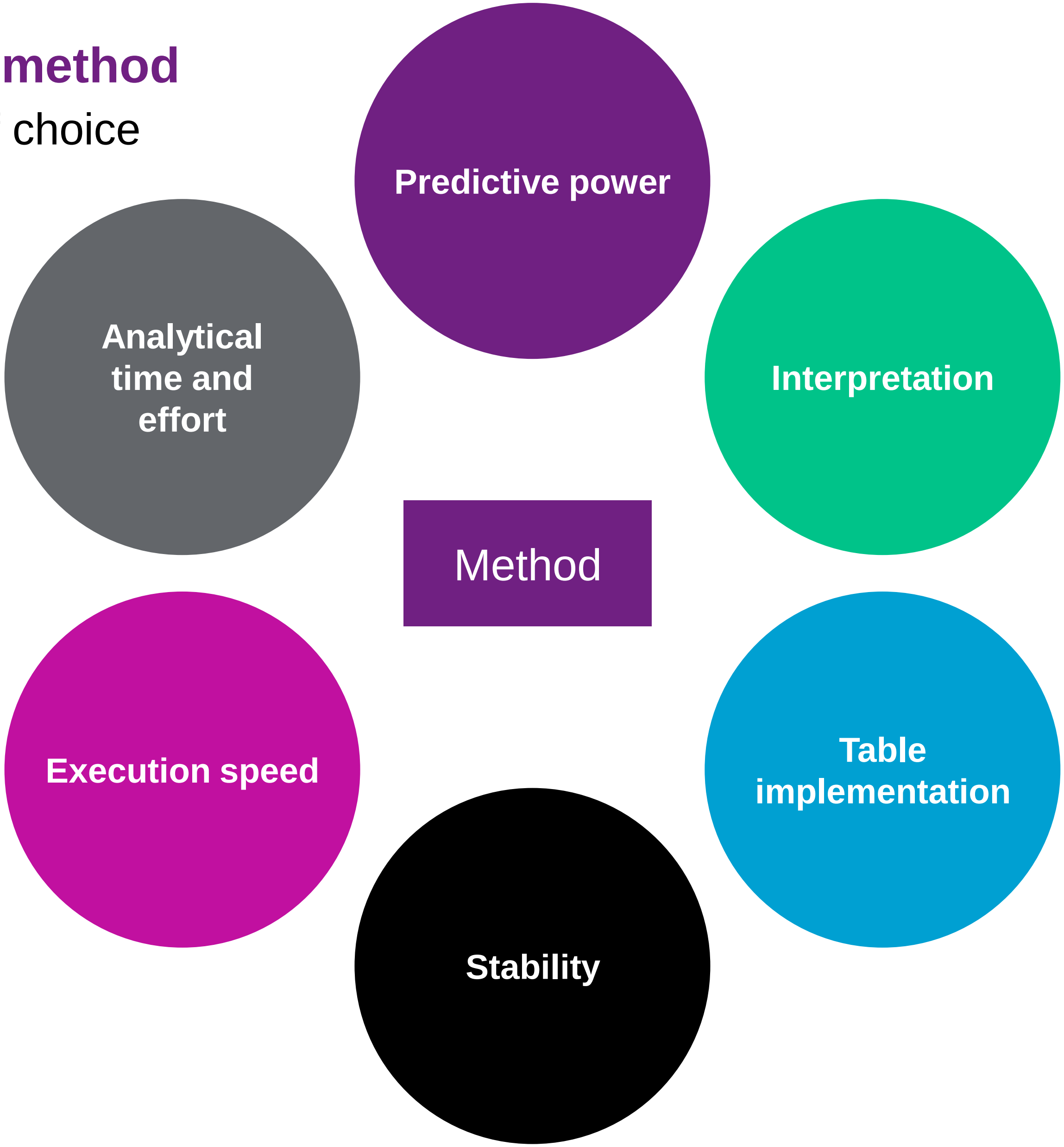


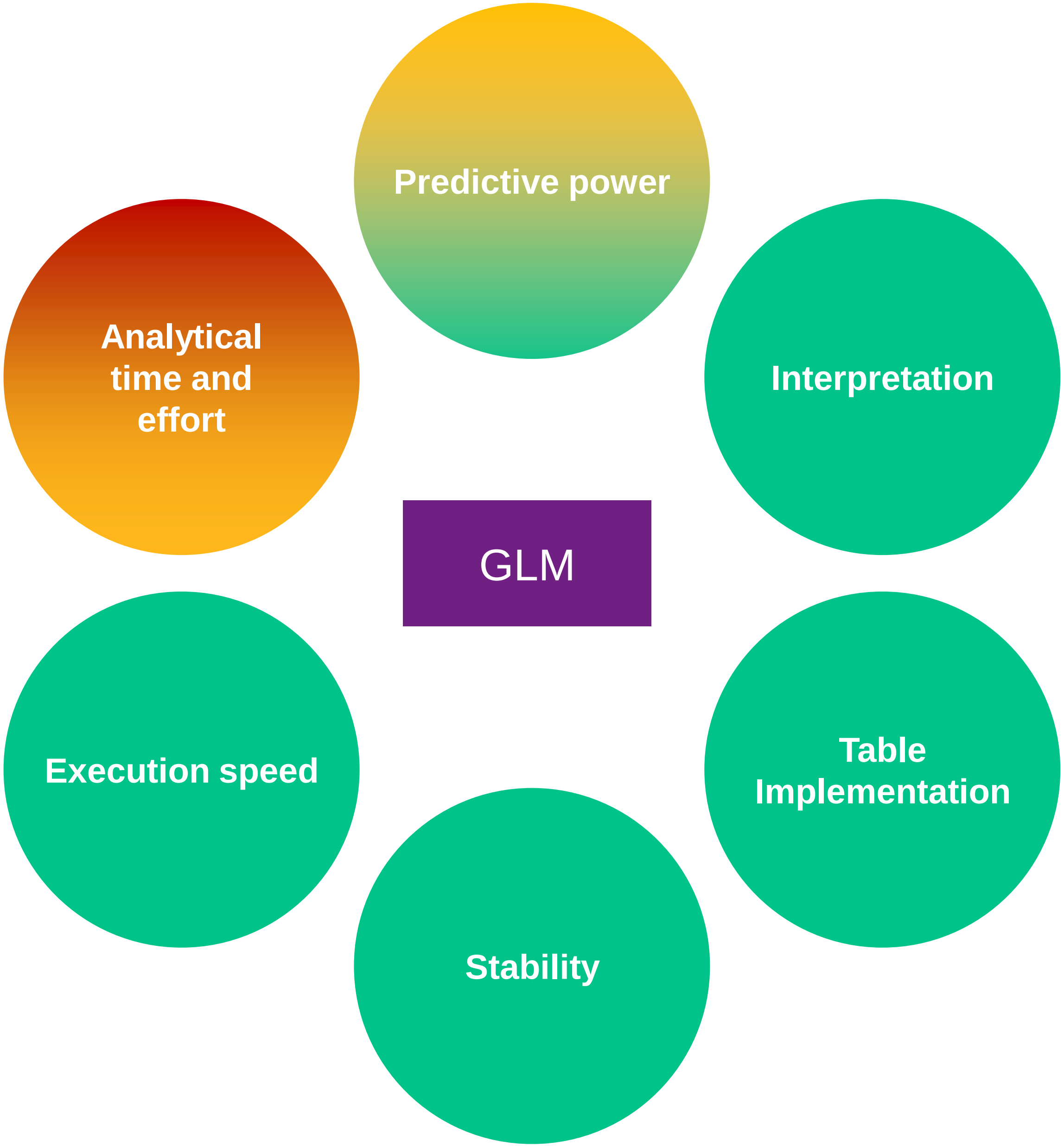
Is there more to it…?

Predictive power

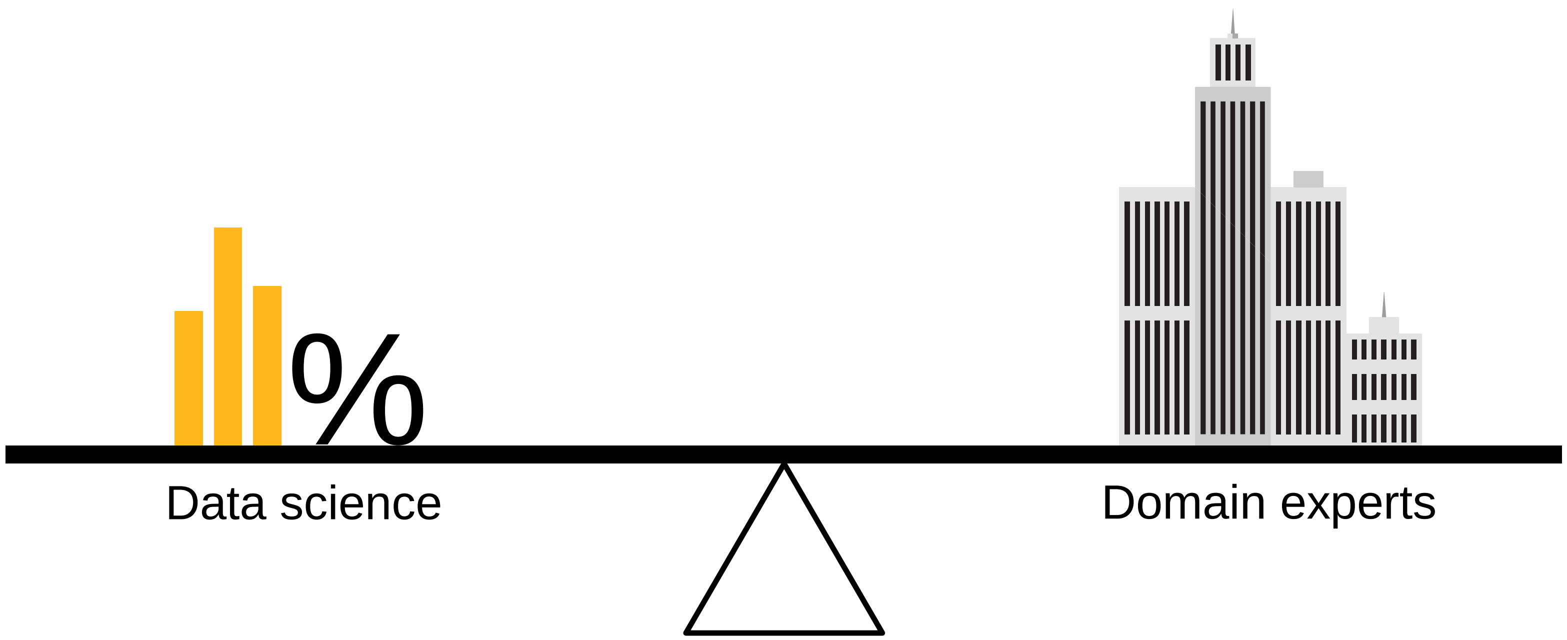
Choosing a method

Dimensions of choice

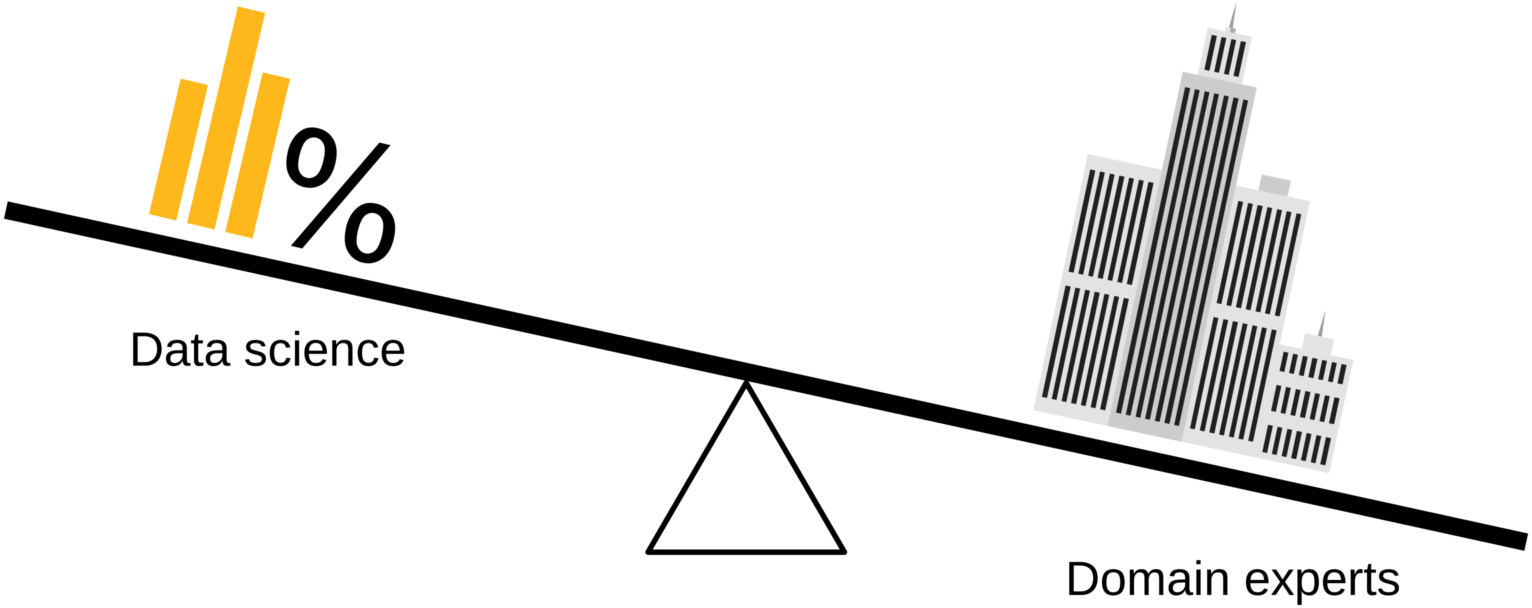



Predictive power
Analytical time and effort
Interpretation
GLM
Execution speed
Table Implementation
Stability

What do you use where?



It’s domain expertise that helps decide



Some machine learning methods

Ensembles

Classifications Trees

"Earth"

Regression Trees

Gradient Boosting Machines

K-nearest Neighbors

Elastic Net

Neural Networks

Naïve Bayes

Random Forests

K-Means Clustering

Principal Components Analysis

Lasso

Support Vector Machines

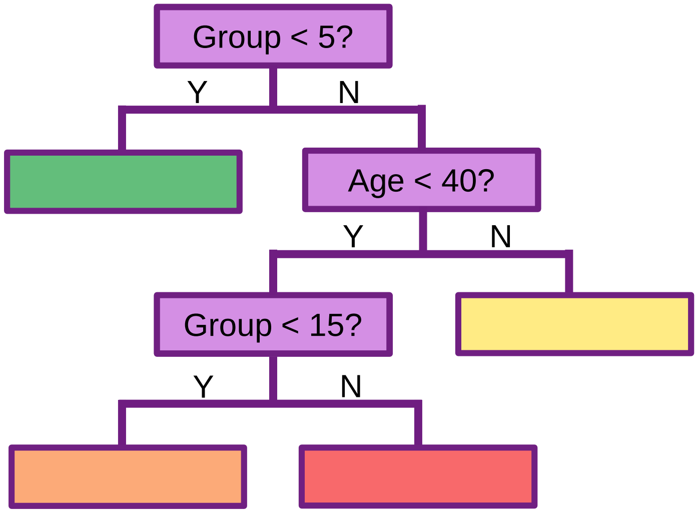
Ridge Regression

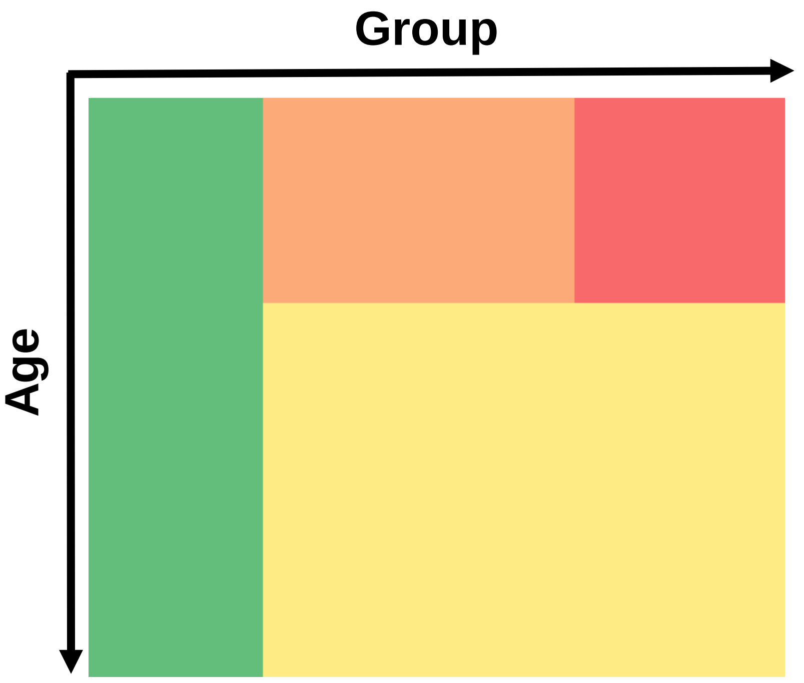
Focus on Trees

Classifications Trees

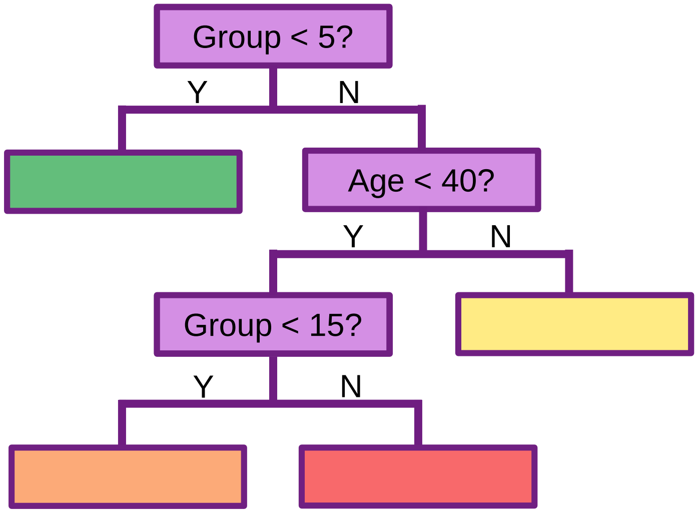
Regression Trees

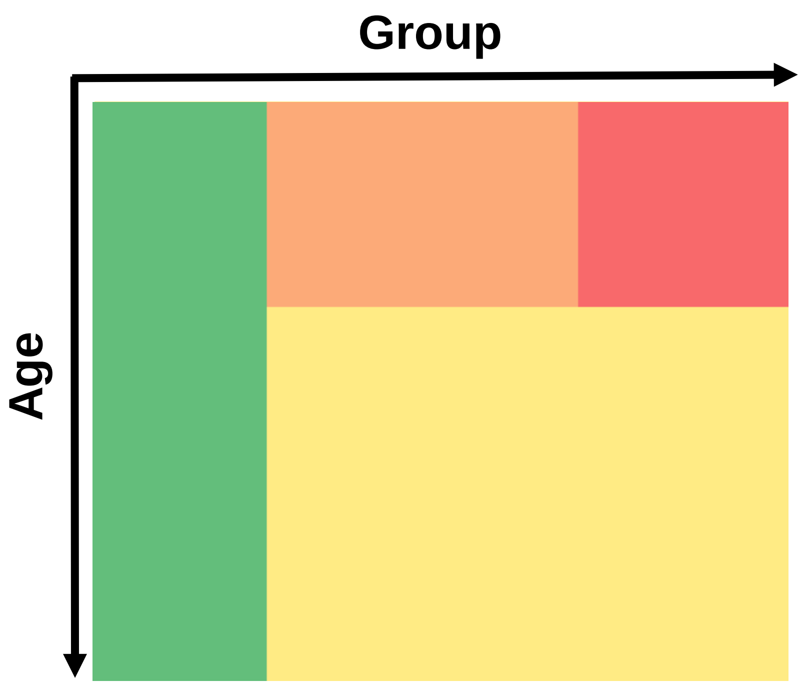
Decision Trees



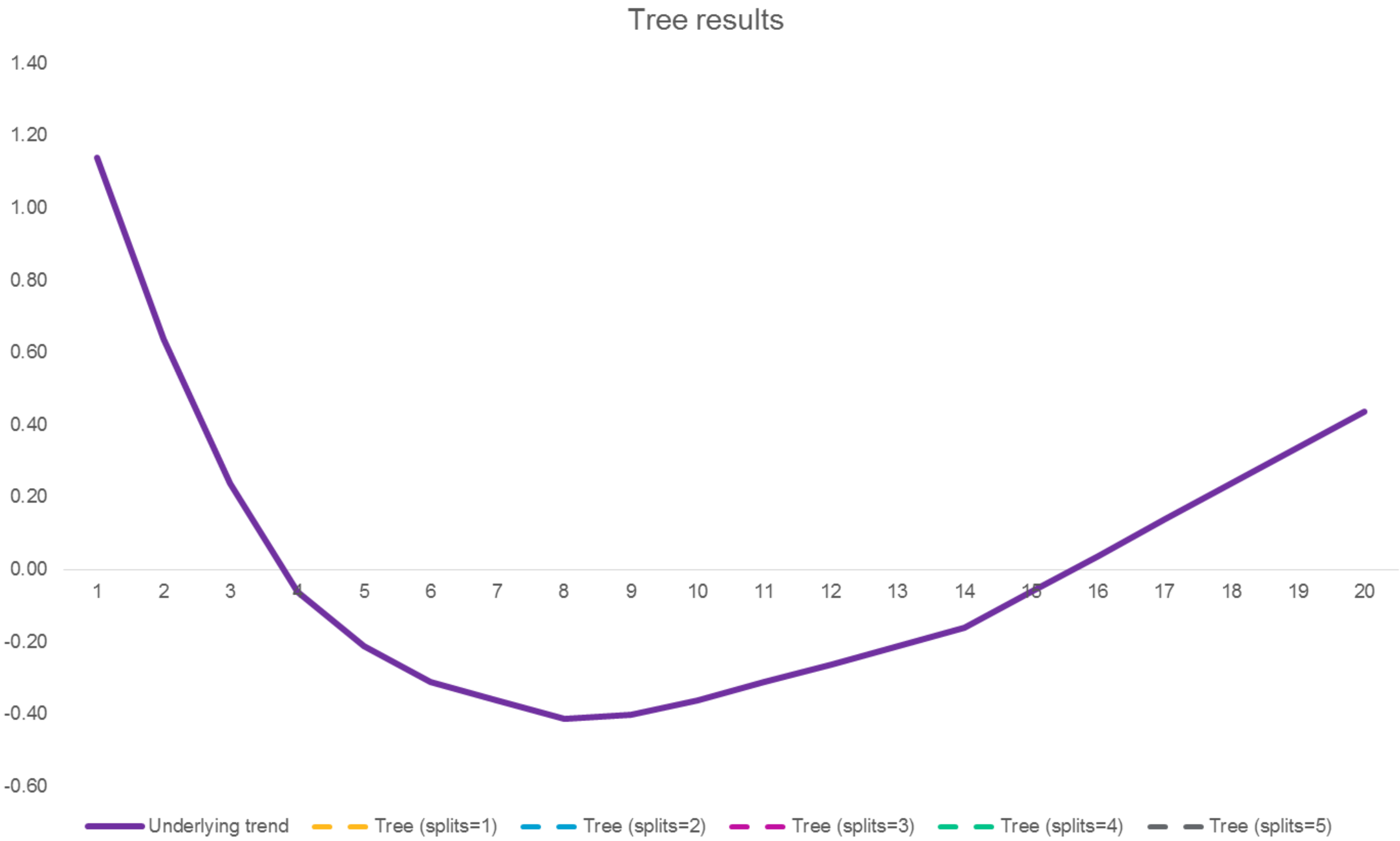


Decision Trees





A simple Tree example



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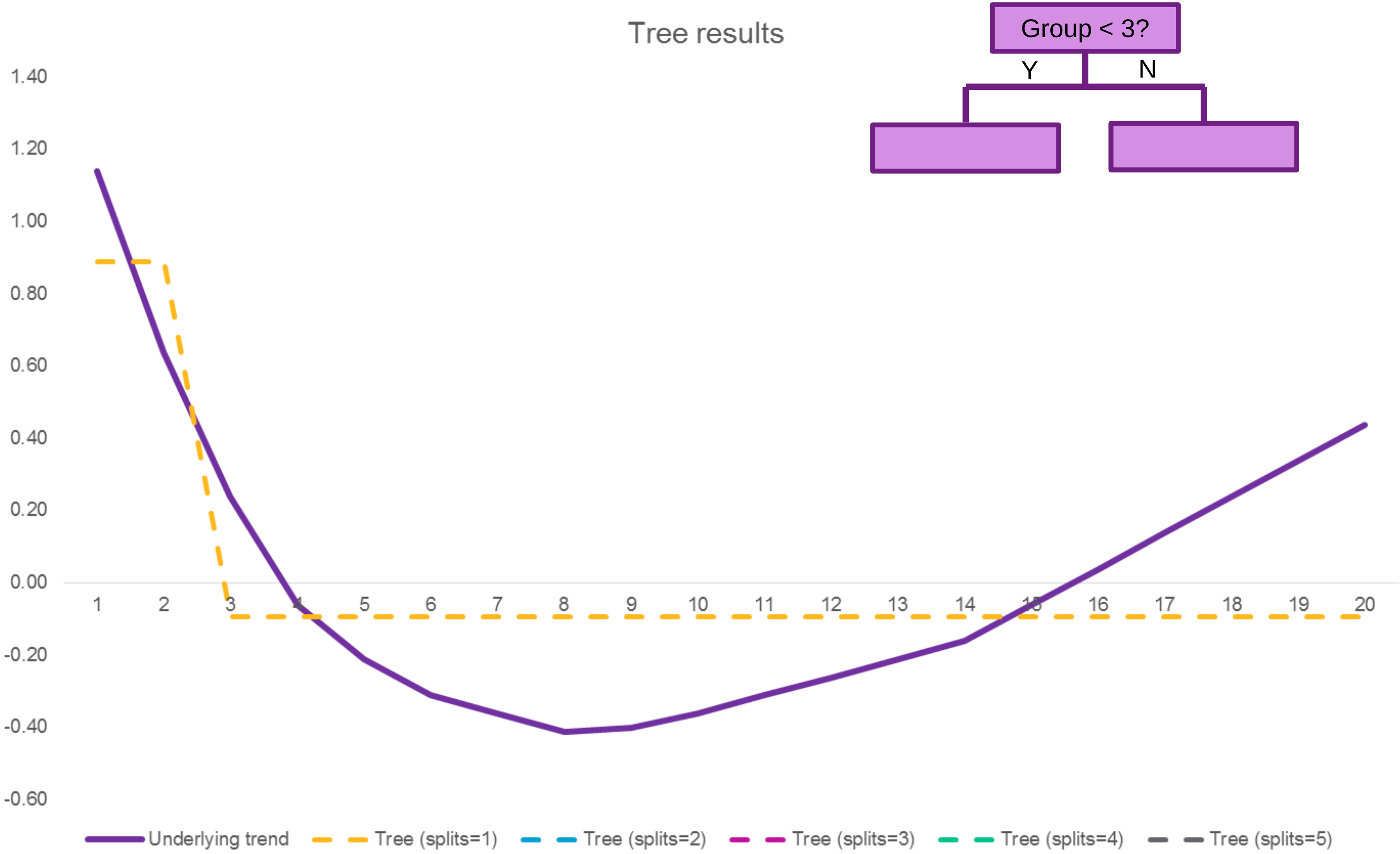

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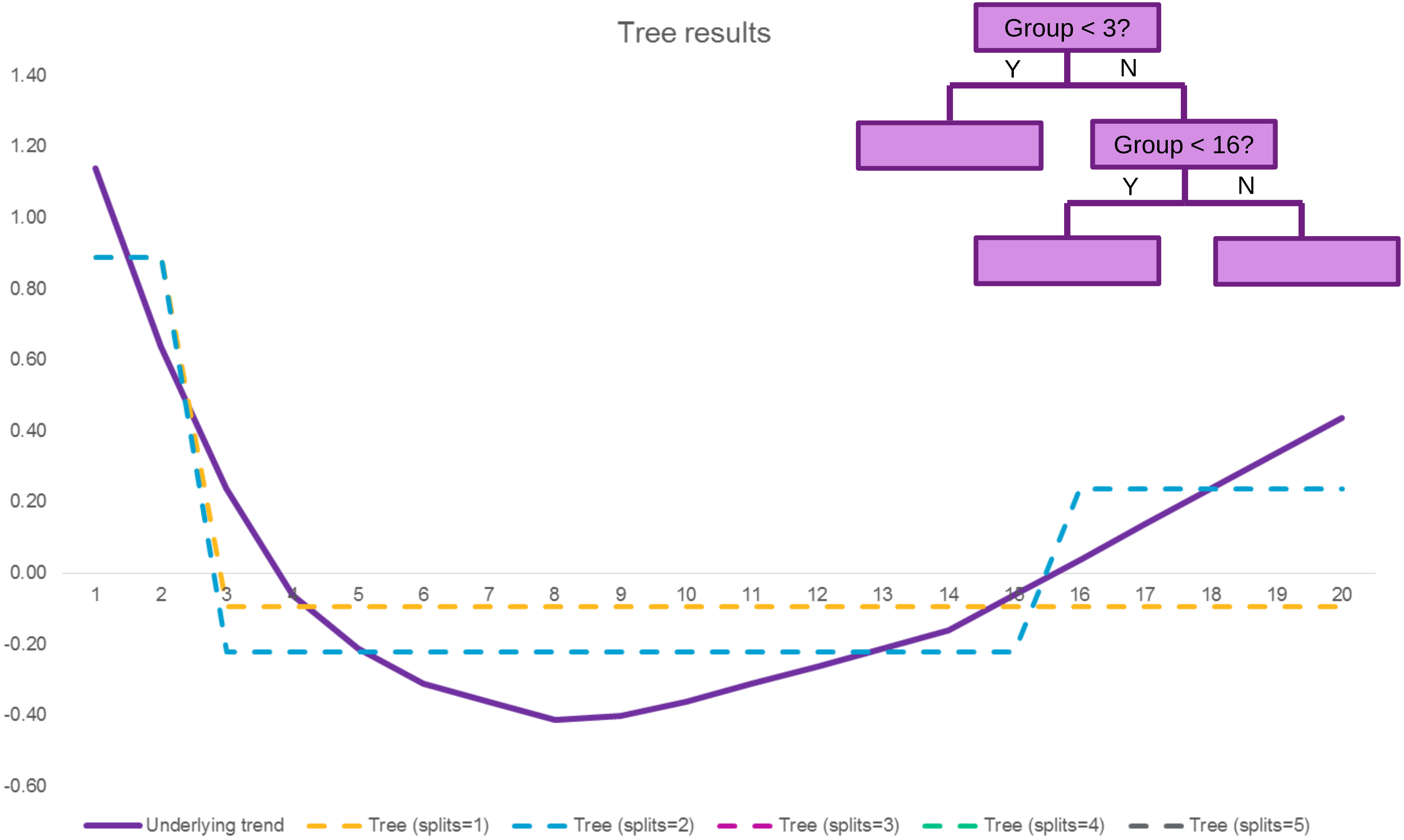
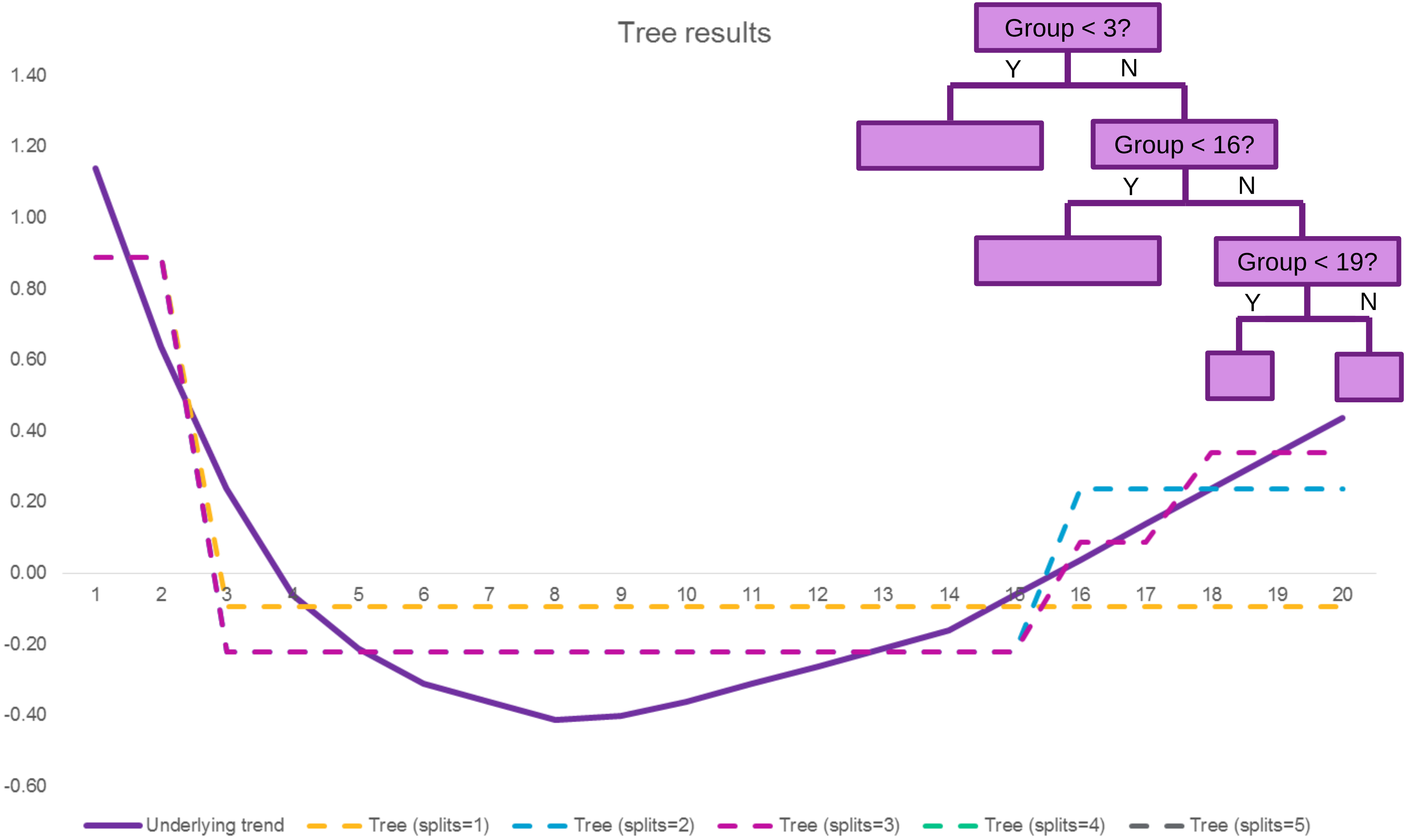
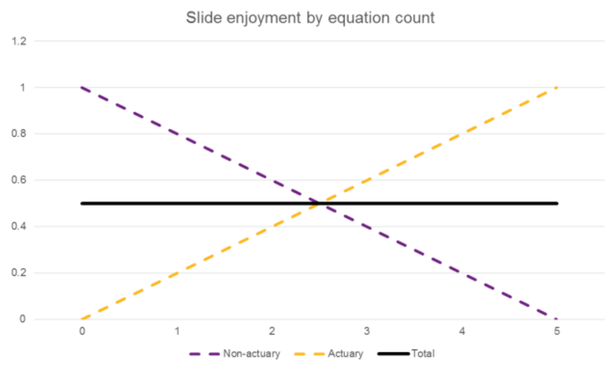


A simple Tree example



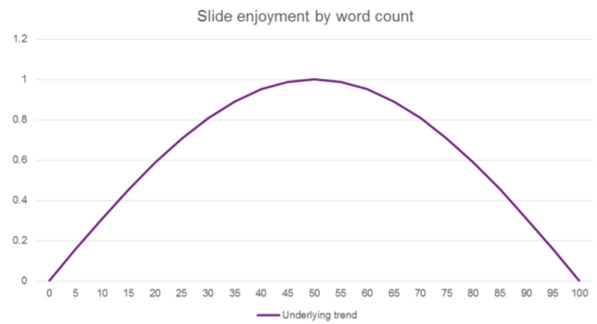
Shortcomings of using trees

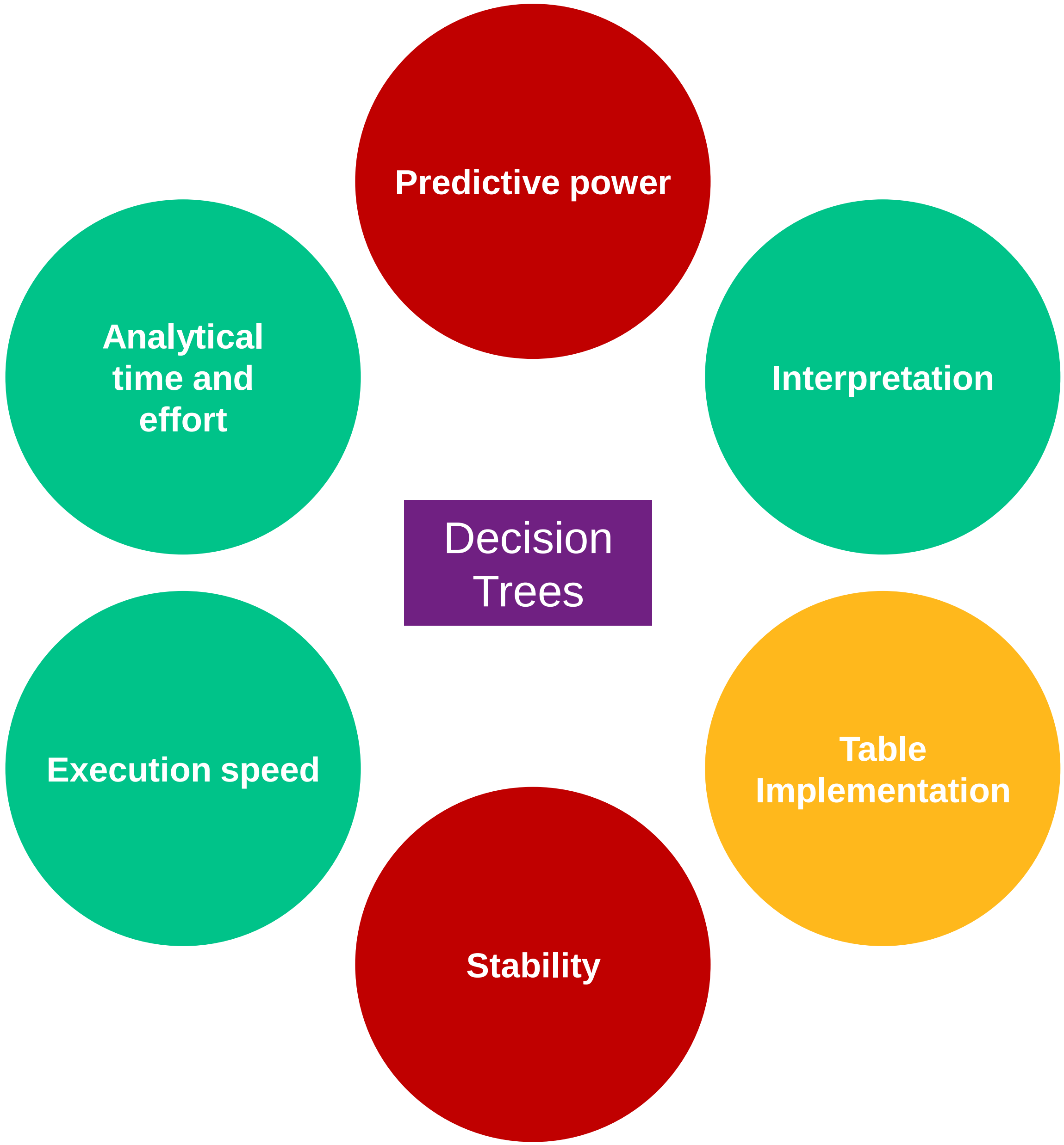
They may miss interactions…



… they may struggles with categorical variables….

…and they can be bad at turning points

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Some machine learning methods

- Ensembles
- Classifications Trees
- "Earth"
- Regression Trees
- Gradient Boosting Machines
- K-nearest Neighbors
- Elastic Net
- Neural Networks
- Naïve Bayes
- Random Forests
- K-Means Clustering
- Principal Components Analysis
- Lasso
- Support Vector Machines
- Ridge Regression

Focus on Random Forests

Random Forests

Random Forests

Tree 1: **Prediction 1** = **Signal 1** + **Noise 1**

Tree 2: **Prediction 2** = **Signal 2** + **Noise 2**

Tree 3: **Prediction 3** = **Signal 3** + **Noise 3**

…

Tree 1000: **Prediction 1000** = **Signal 1000** + **Noise 1000**

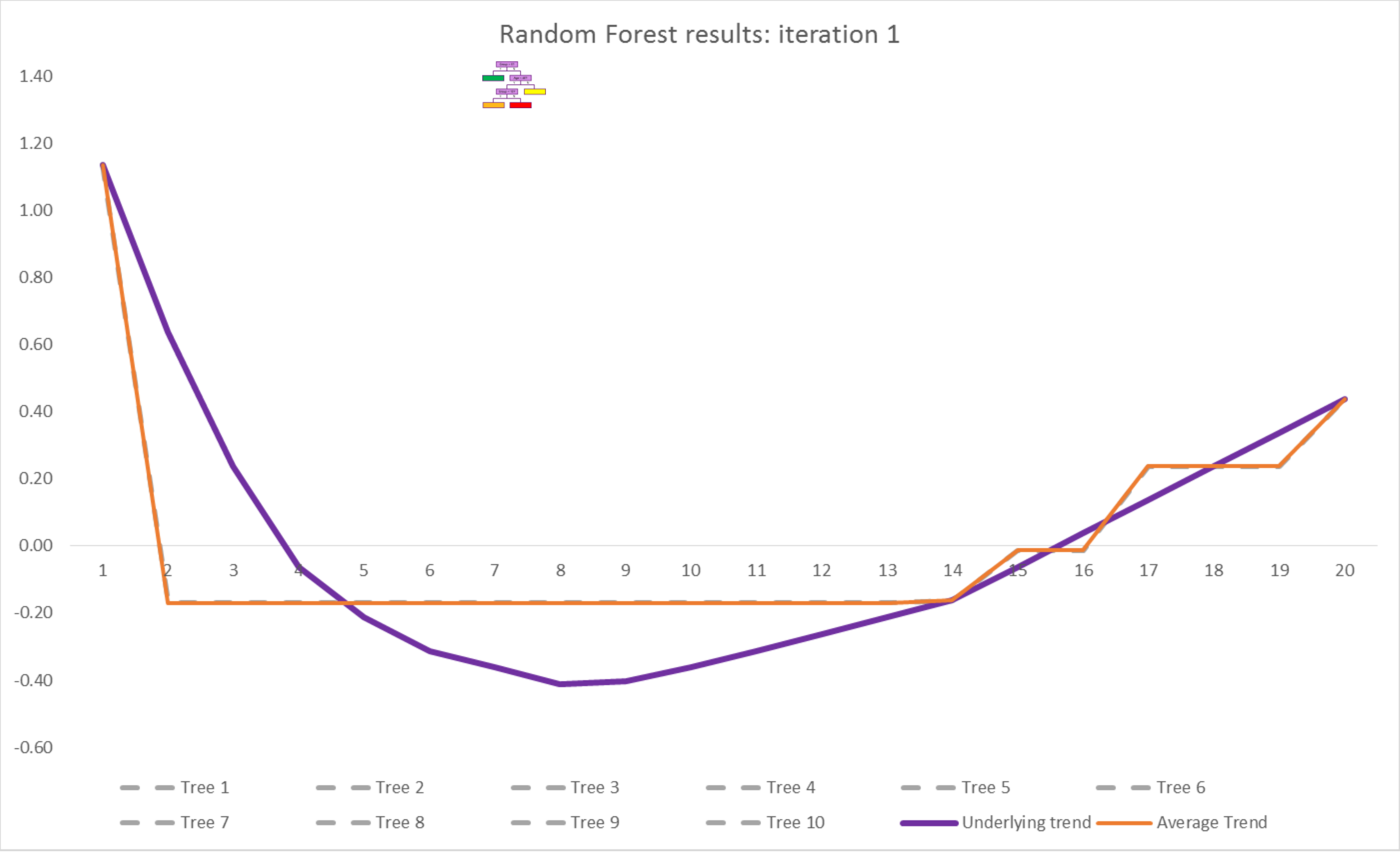
Random Forest:

Prediction = AVERAGE(Tree Predictions)

= **AVERAGE(Tree Signal)** + **AVERAGE(Tree Noise)**

- **Average Noise → 0** if the trees are independent
- Independence of trees achieved by fitting each tree to:
  - Random subset of data (bootstrap sample)
  - Random subset of factors
- **Average Signal → Underlying trend**, provided trees are complex enough to represent it
- This is **bagging** (**b**ootstrap **agg**regation) – fit **lots** of independent models and take an average

A simple Random Forest example



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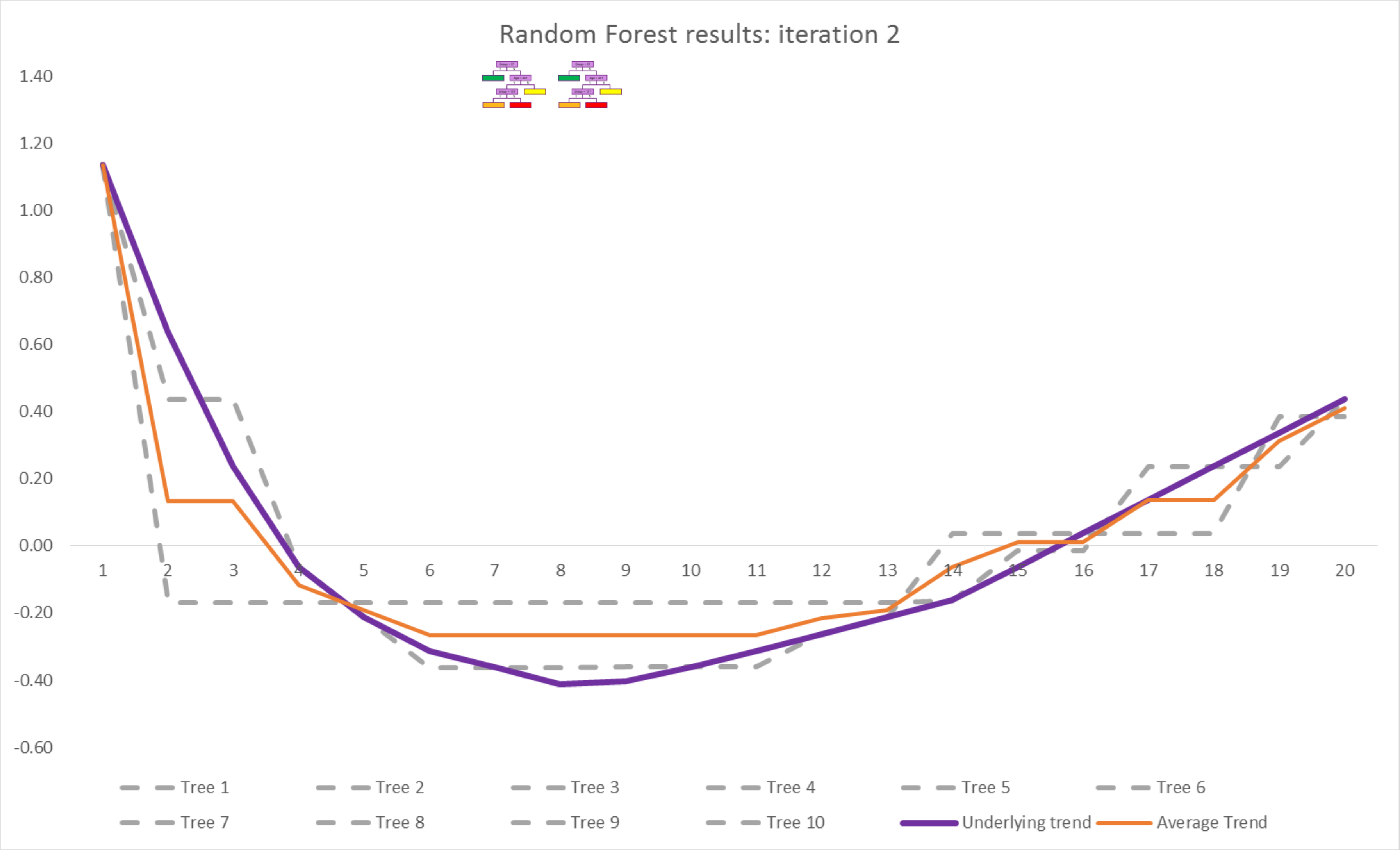

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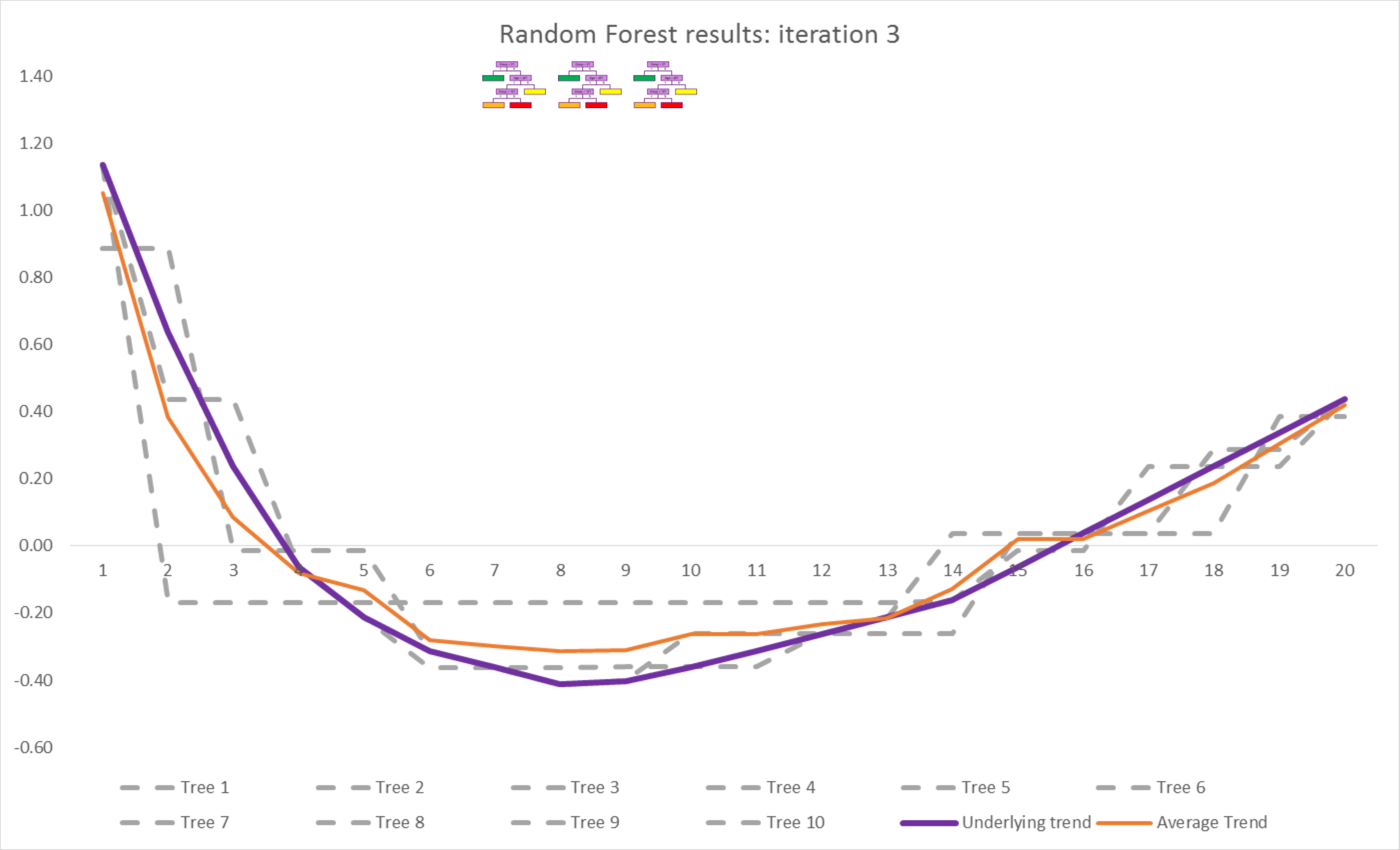

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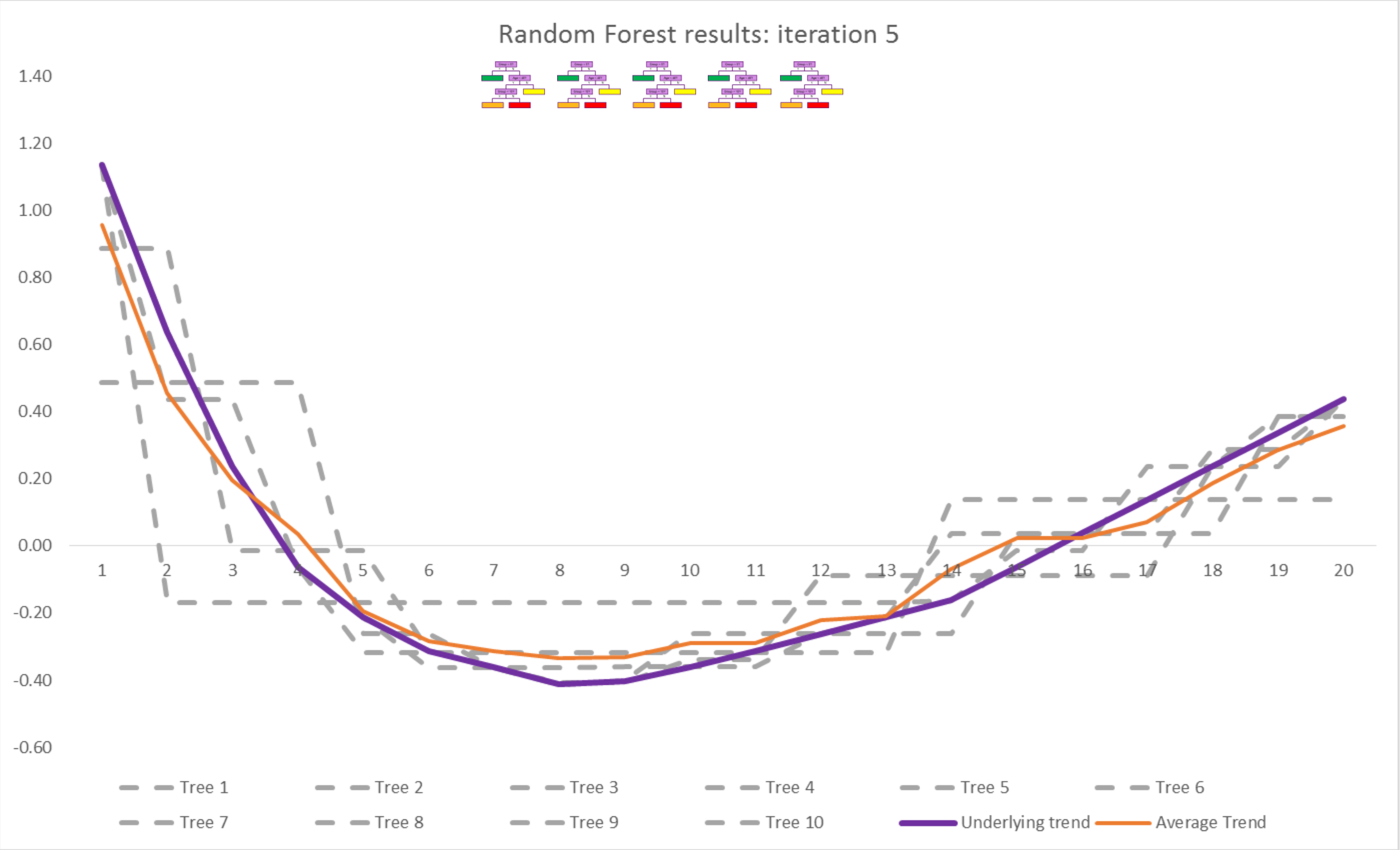

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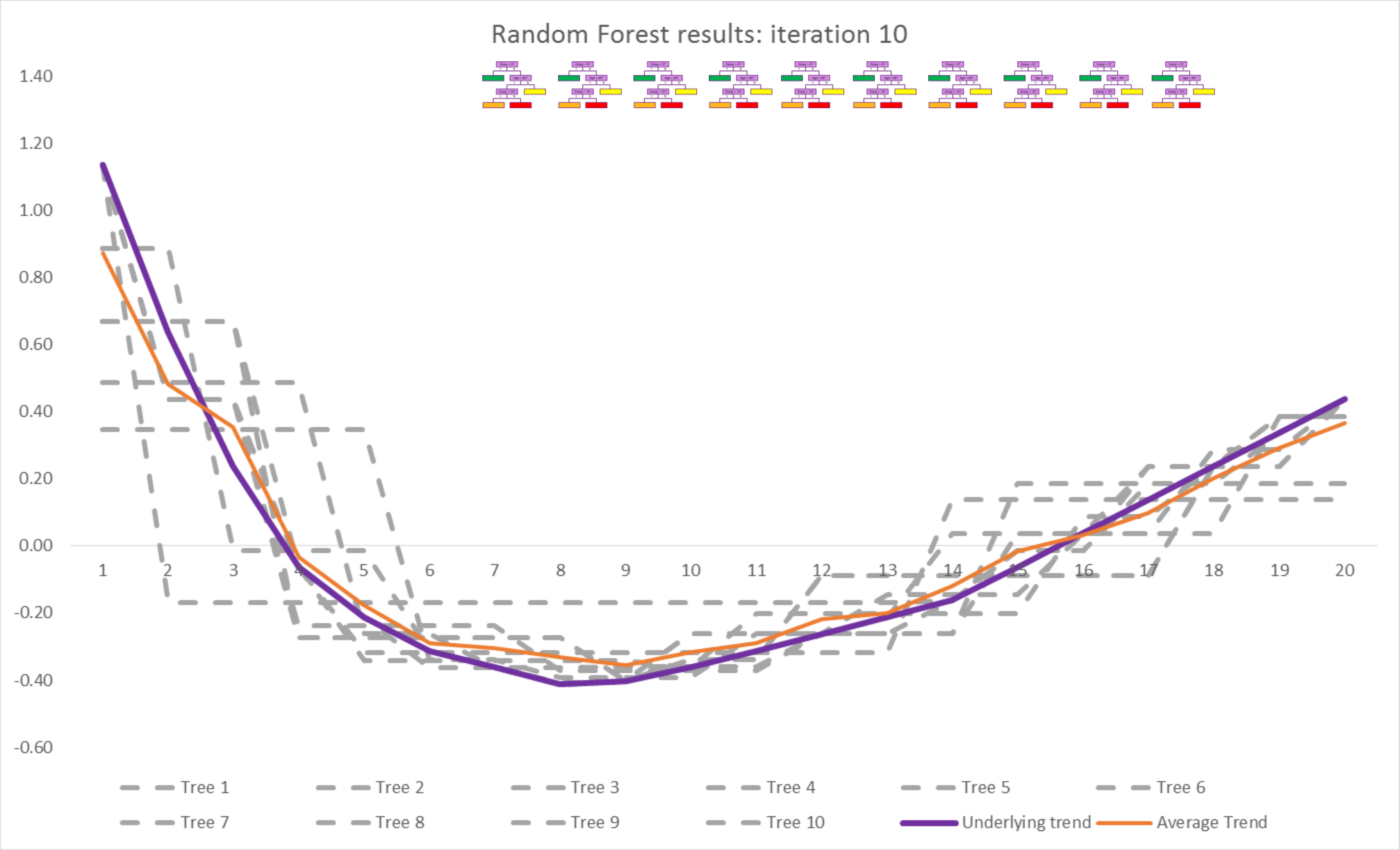

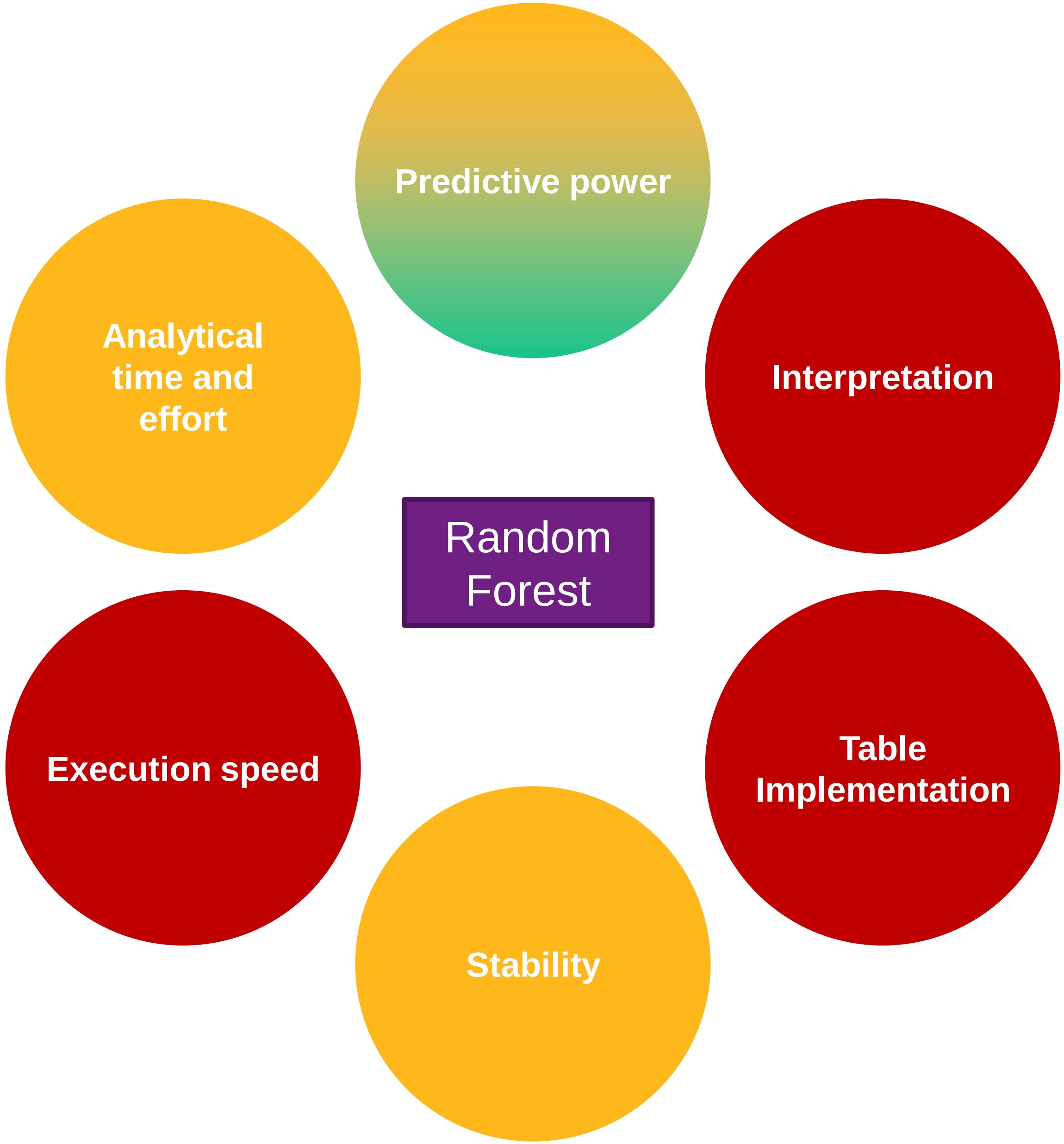
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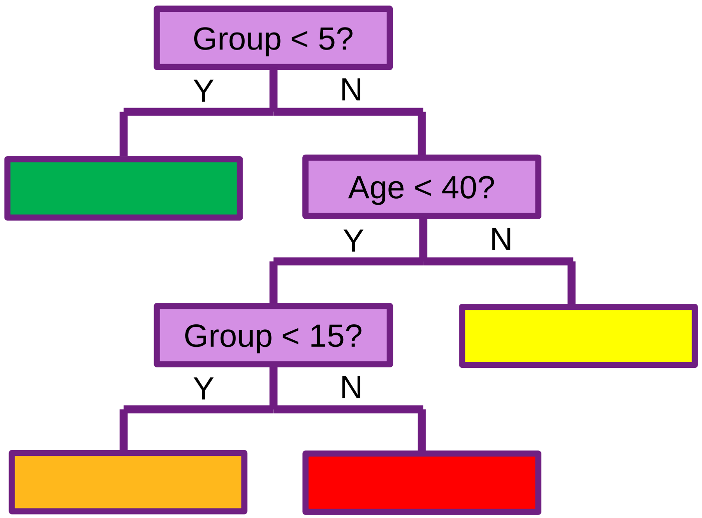
Focus on Gradient Boosting Machines

Gradient Boosting Machines

Gradient Boosted Machine or "GBM"

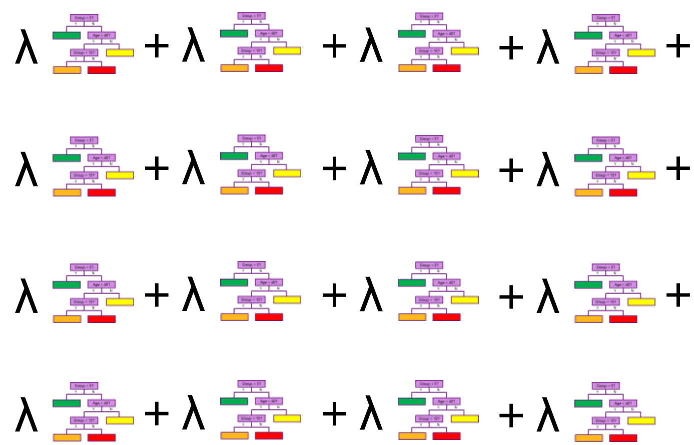
A tree

$$f_i(x)$$



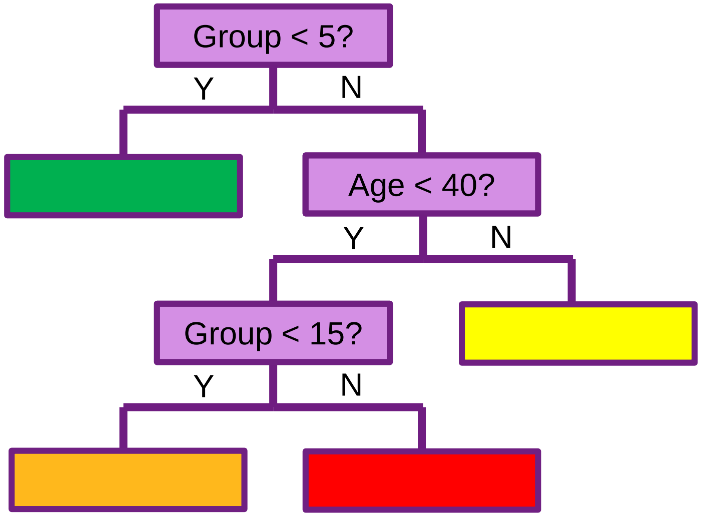
A GBM

$$f(x) = \lambda \sum_{n=1}^{N} f_n(x)$$

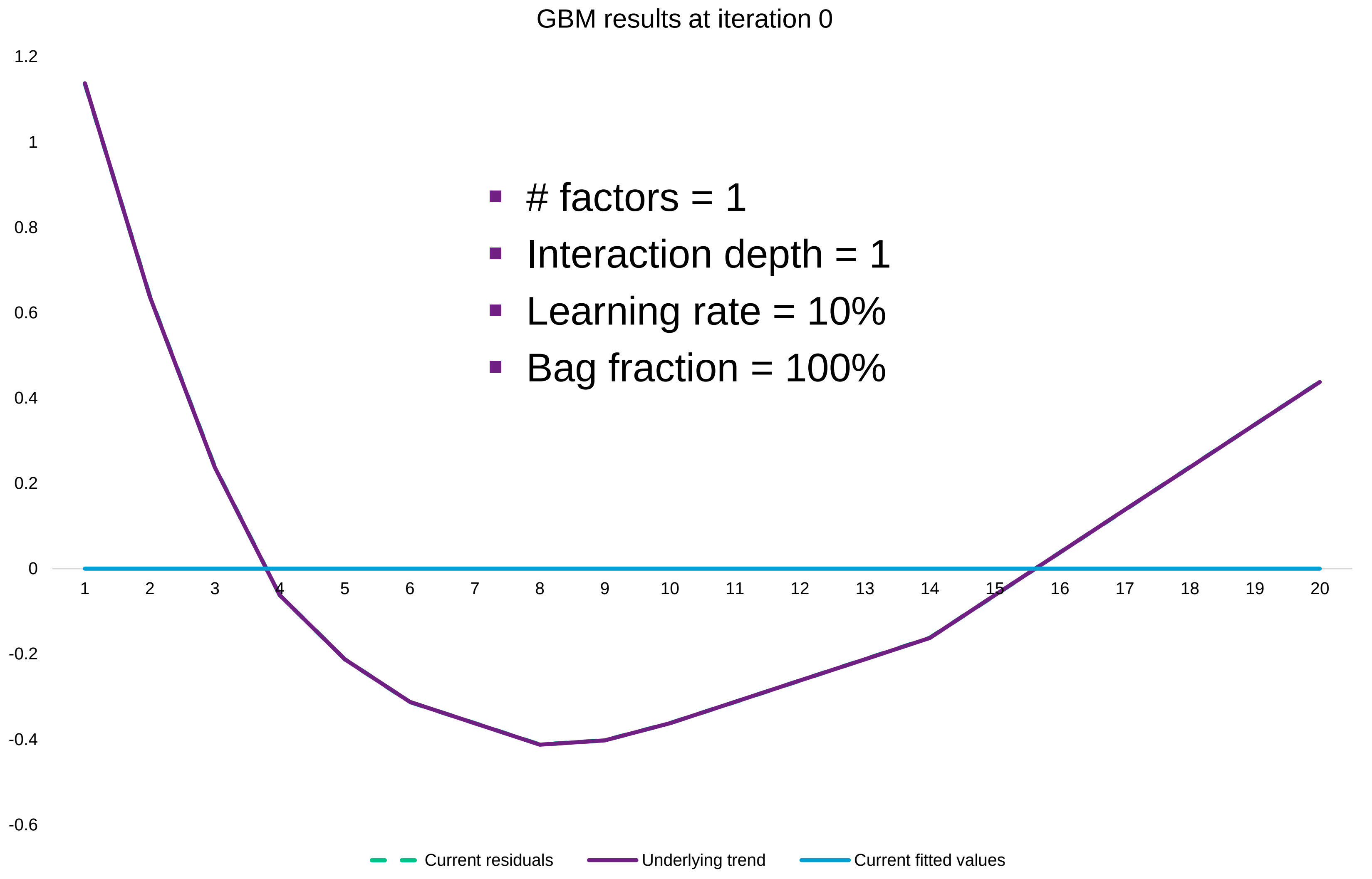


Four main assumptions

- λ **Learning rate / "shrinkage"**
  - Amount by which the old model predictions are varied for the next model iteration
  - New model = Old + (Prediction x Learning rate)
- **Interaction depth**
  - Number of splits allowed on each tree (or the number of terminal nodes – 1)
- **N Number of trees** (iterations) allowed
- **Bag fraction**
  - Trees are fitted to a subset of the data (the bag fraction) on a randomized basis
  - Additional noise-reduction can be achieved by using a random subset of the available factors at each iteration

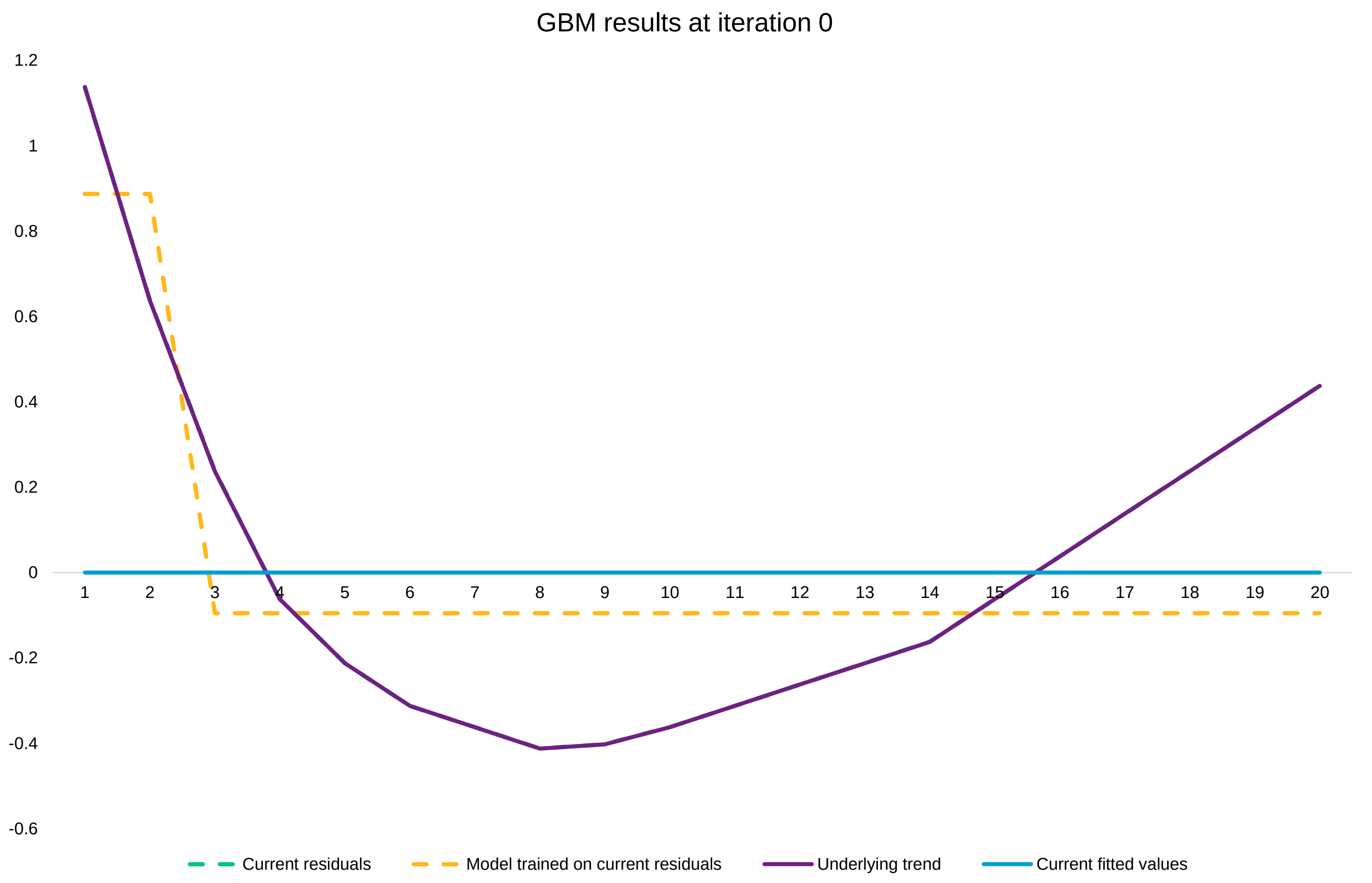


A simple GBM example



- # factors = 1
- Interaction depth = 1
- Learning rate = 10%
- Bag fraction = 100%

A simple GBM example



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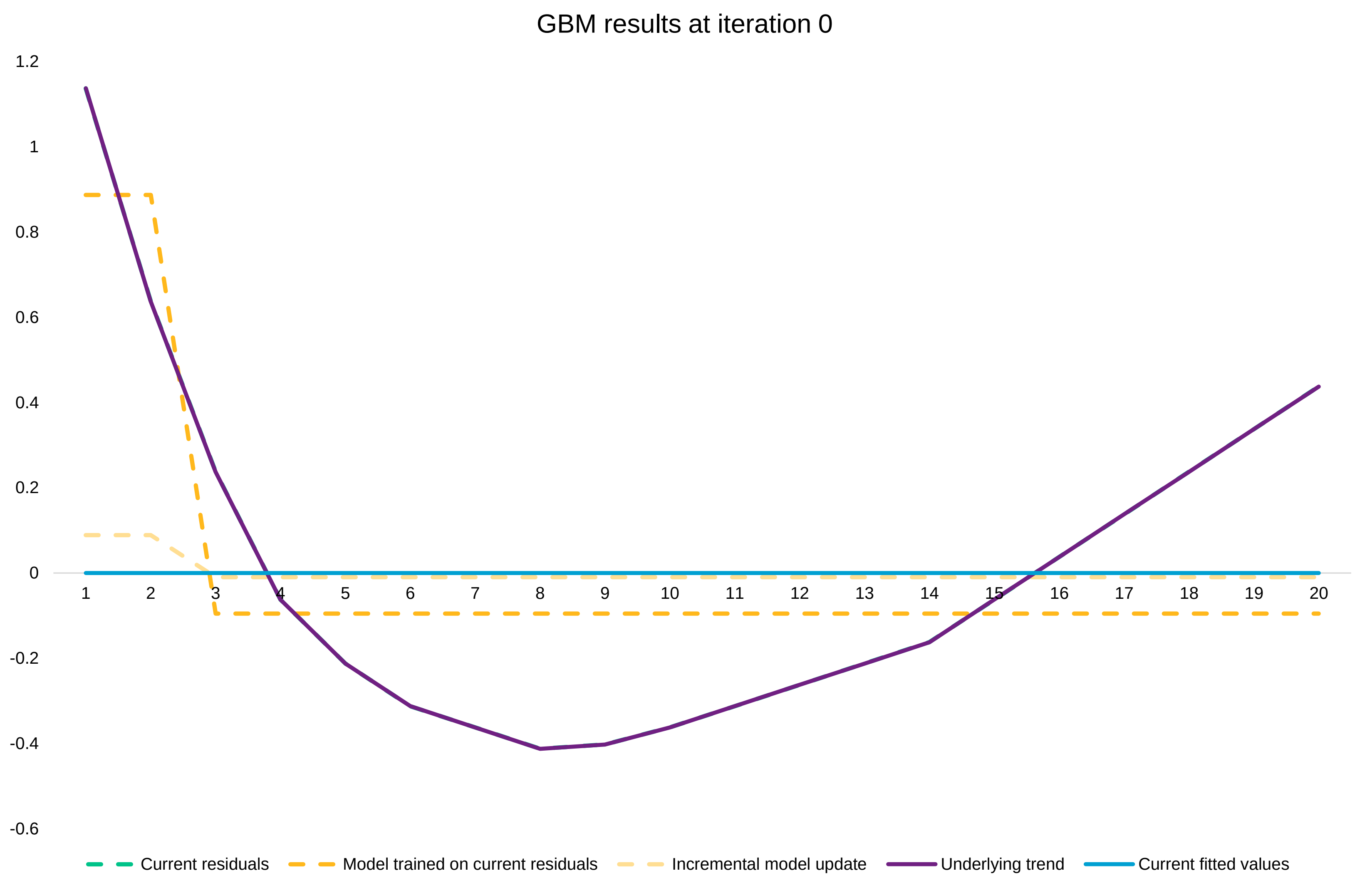

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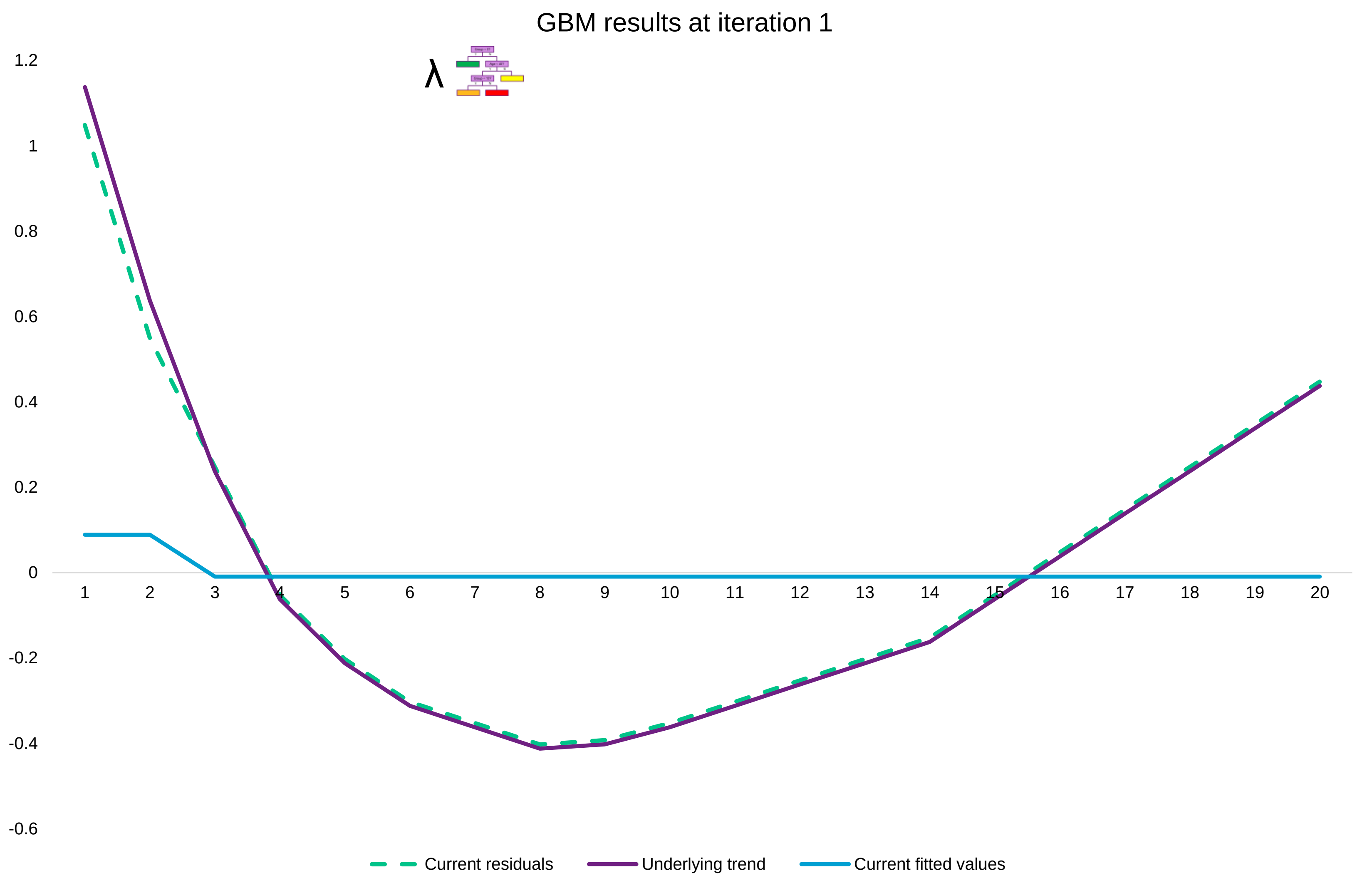

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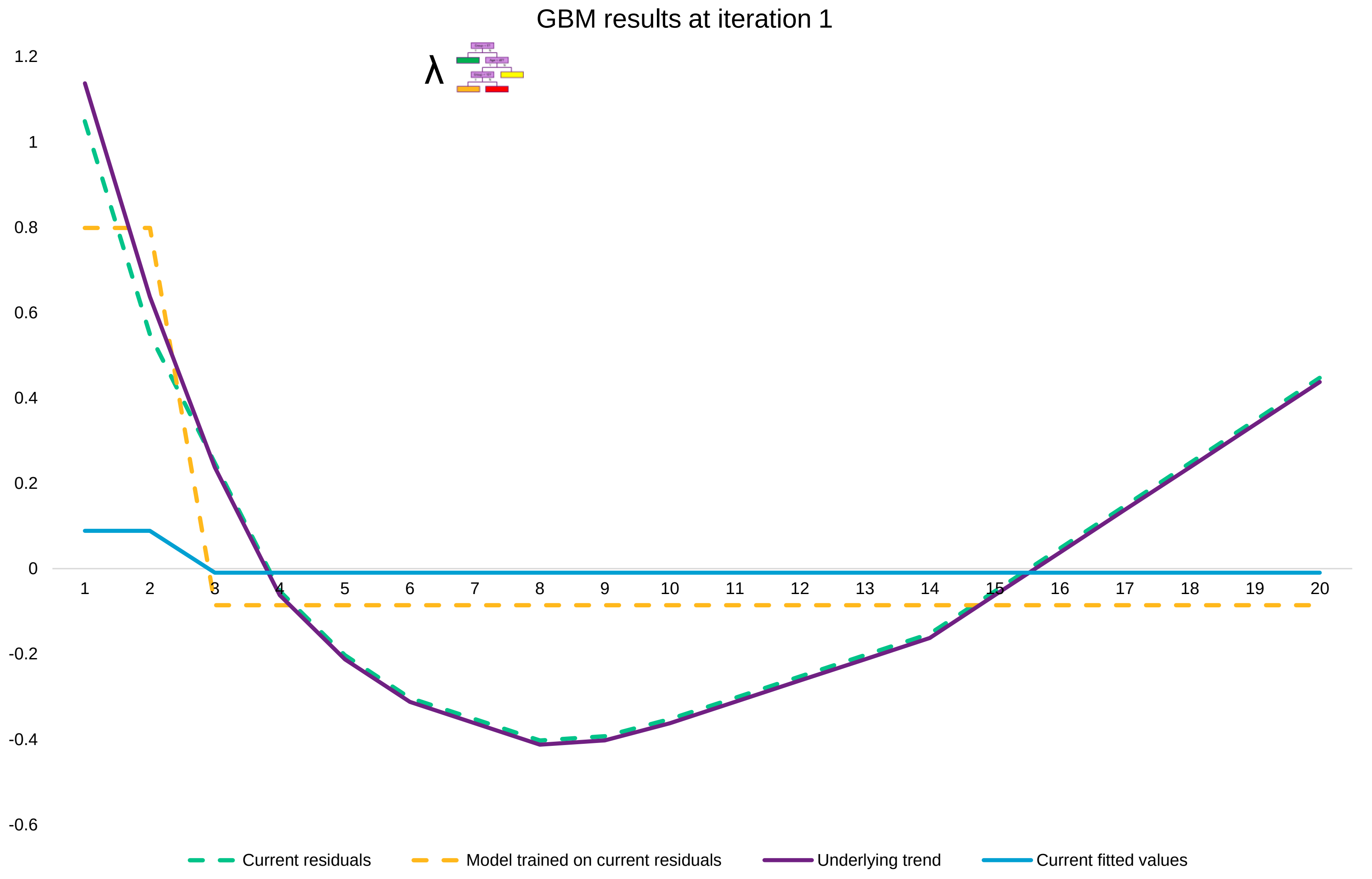

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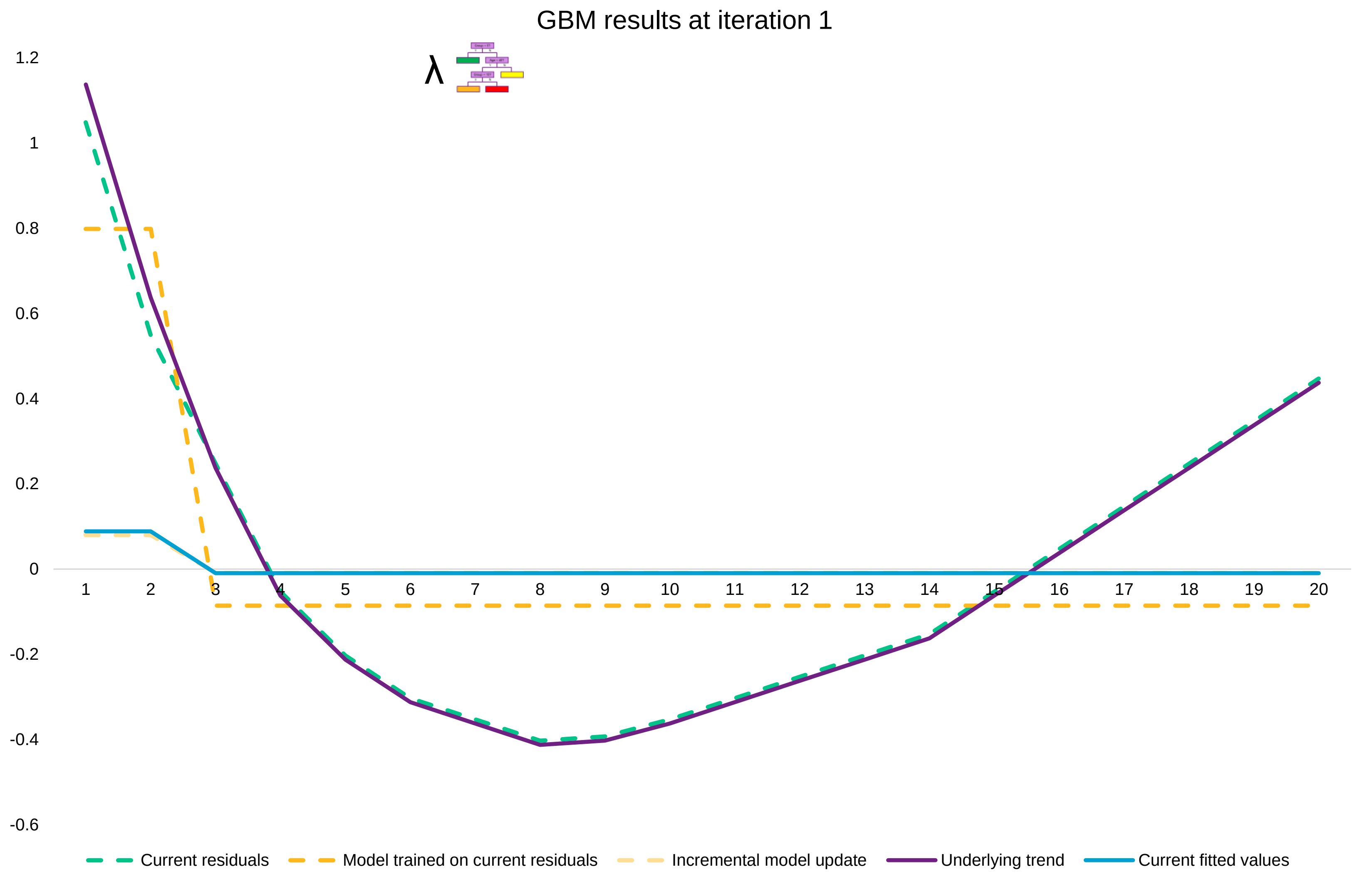

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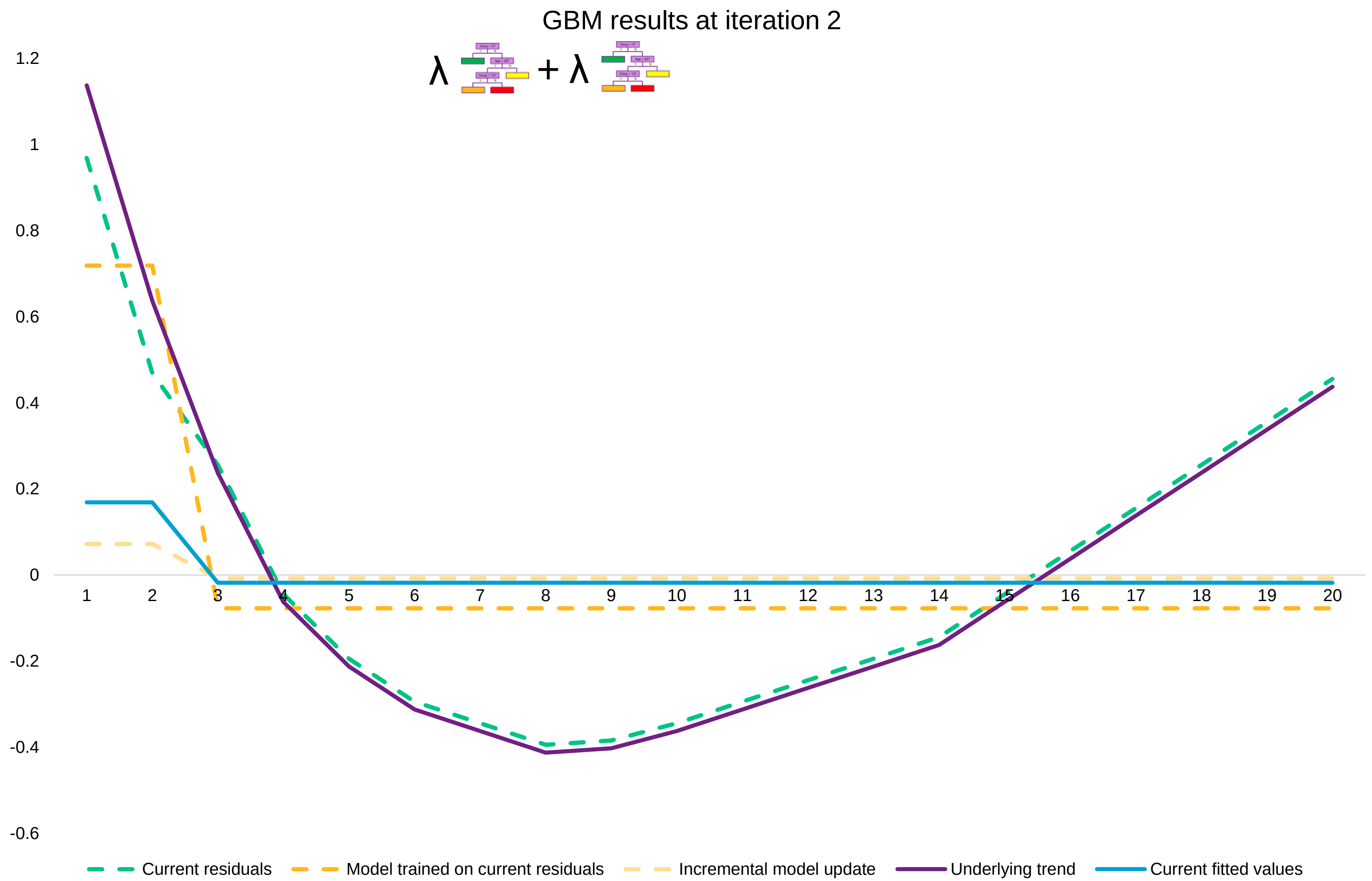

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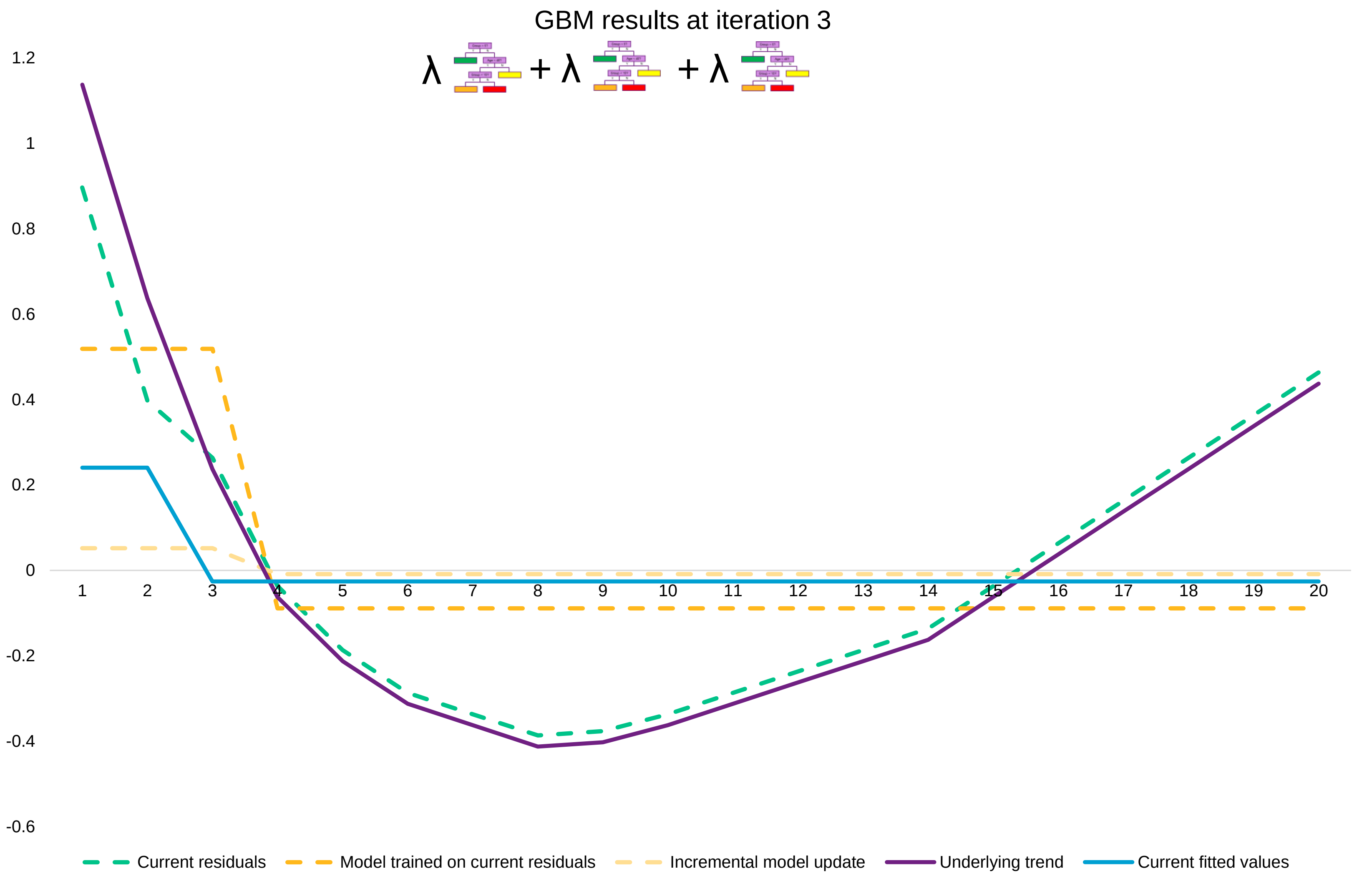

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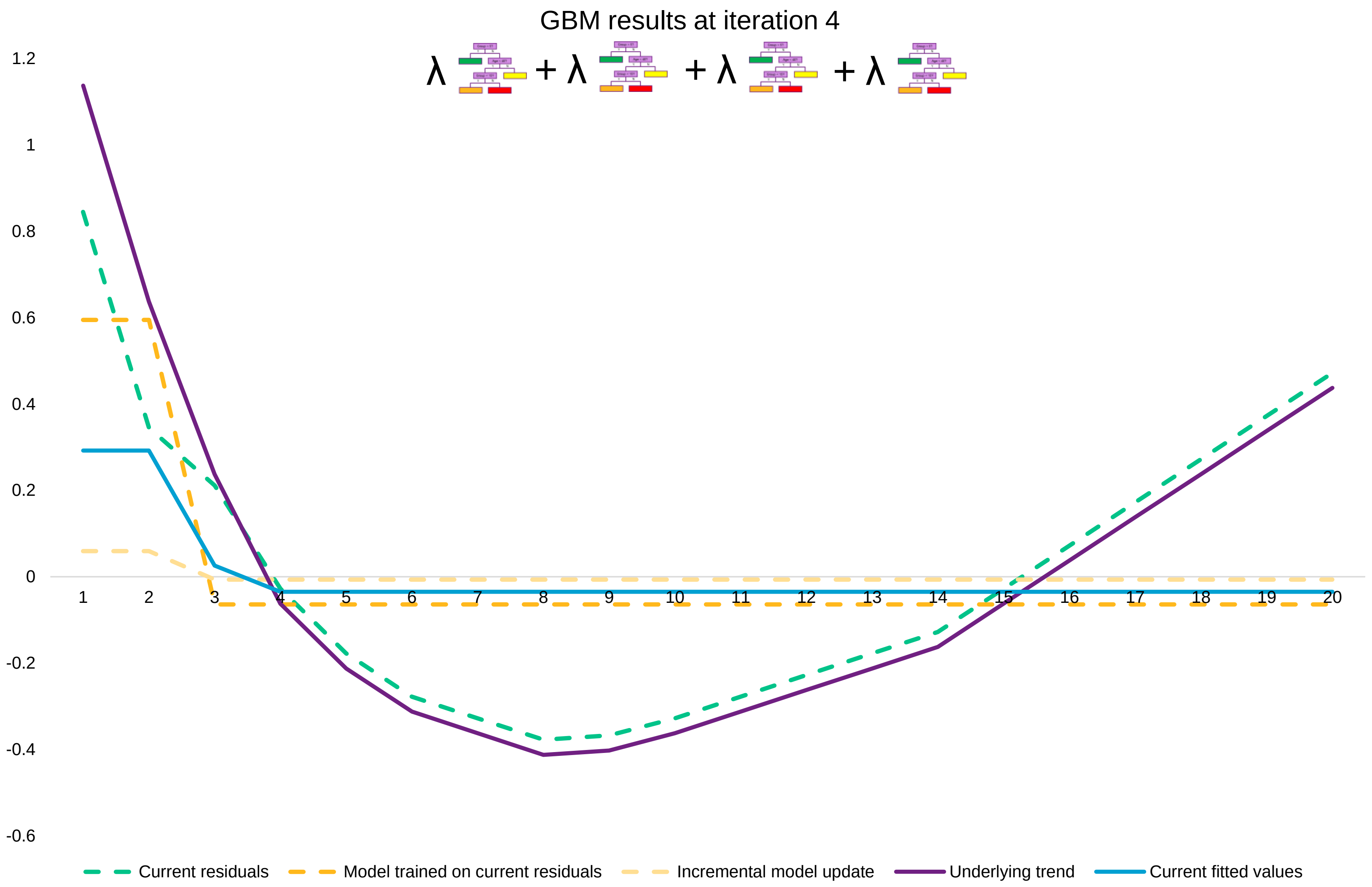

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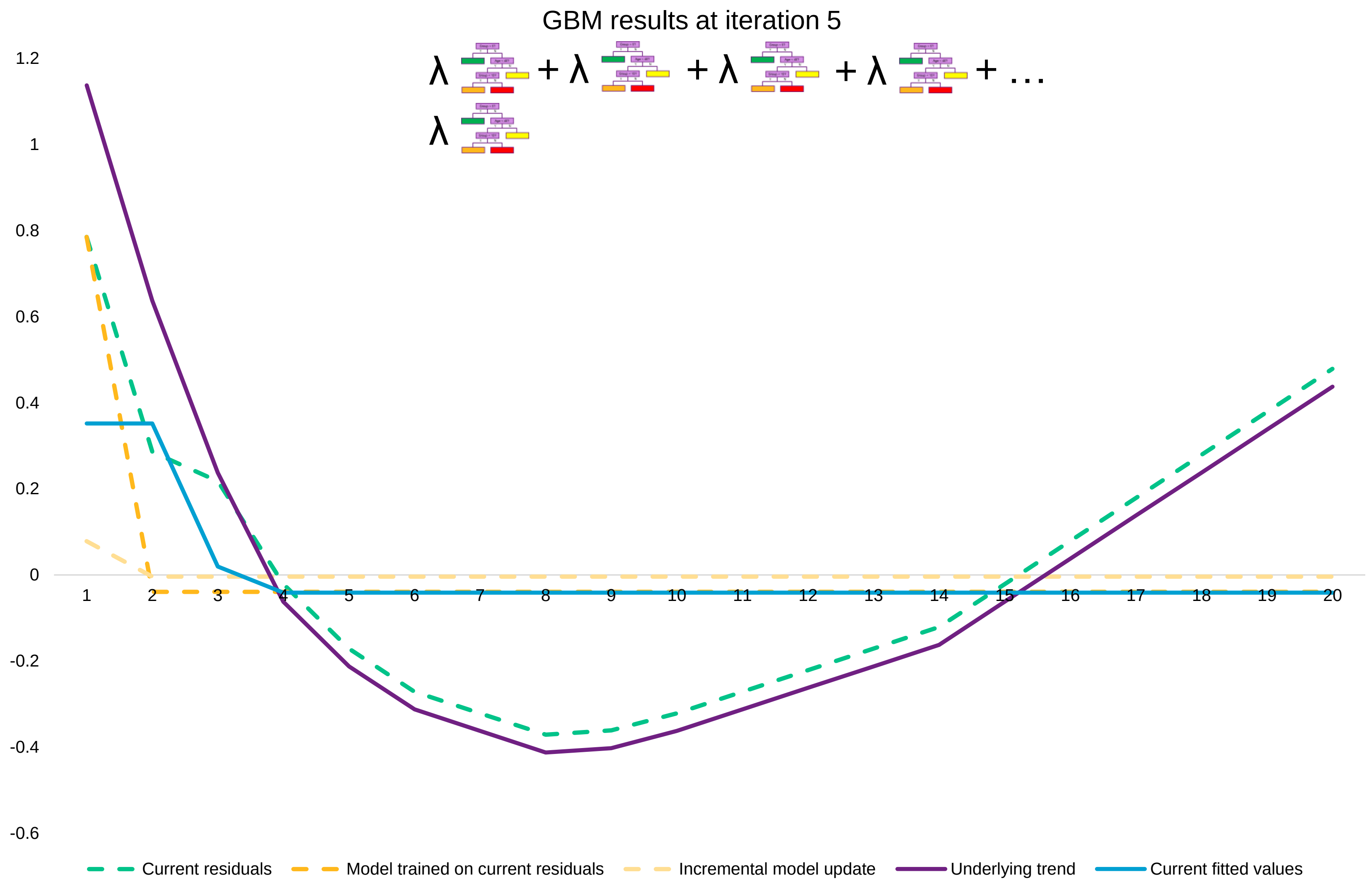
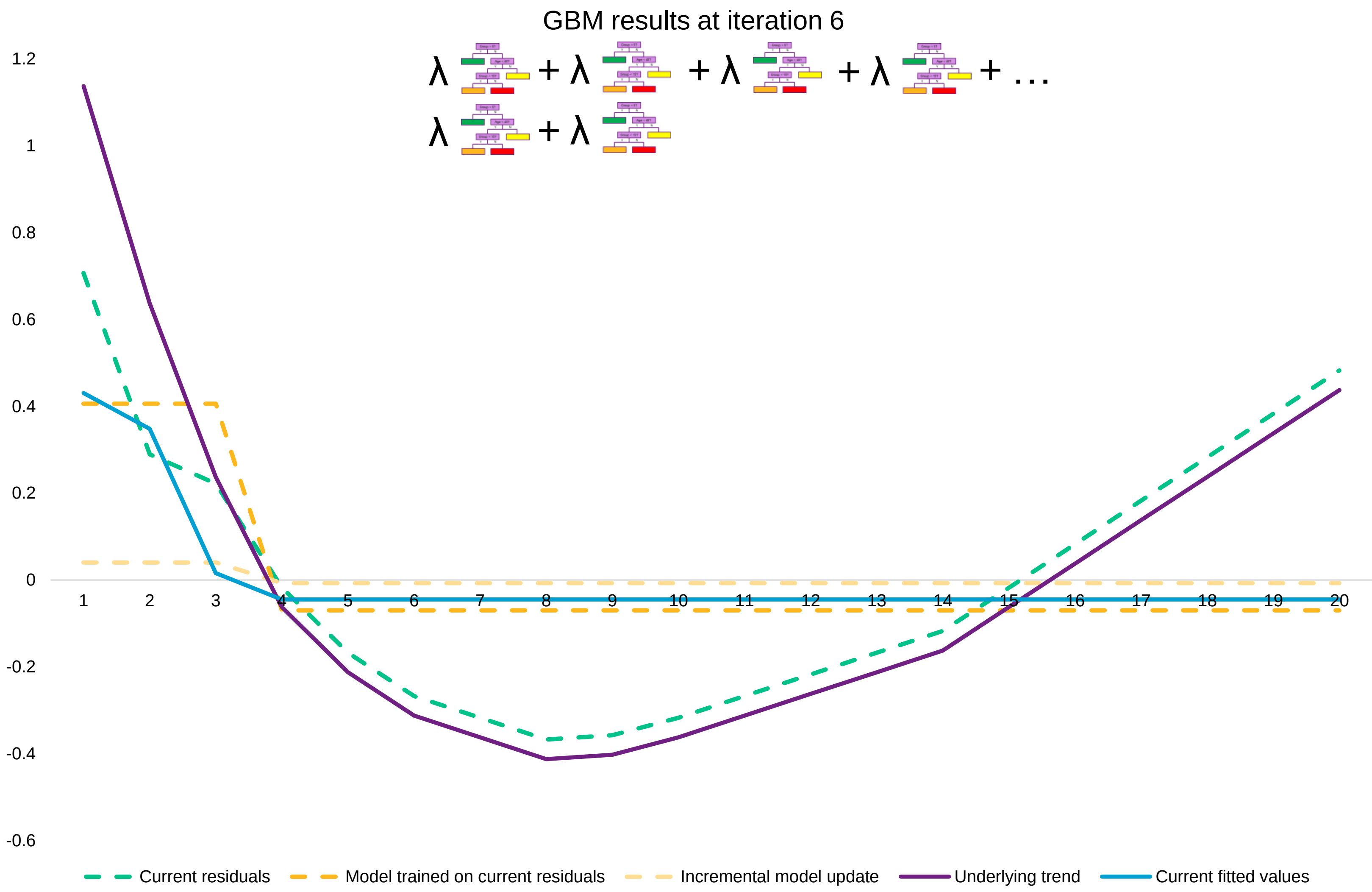


A simple GBM example



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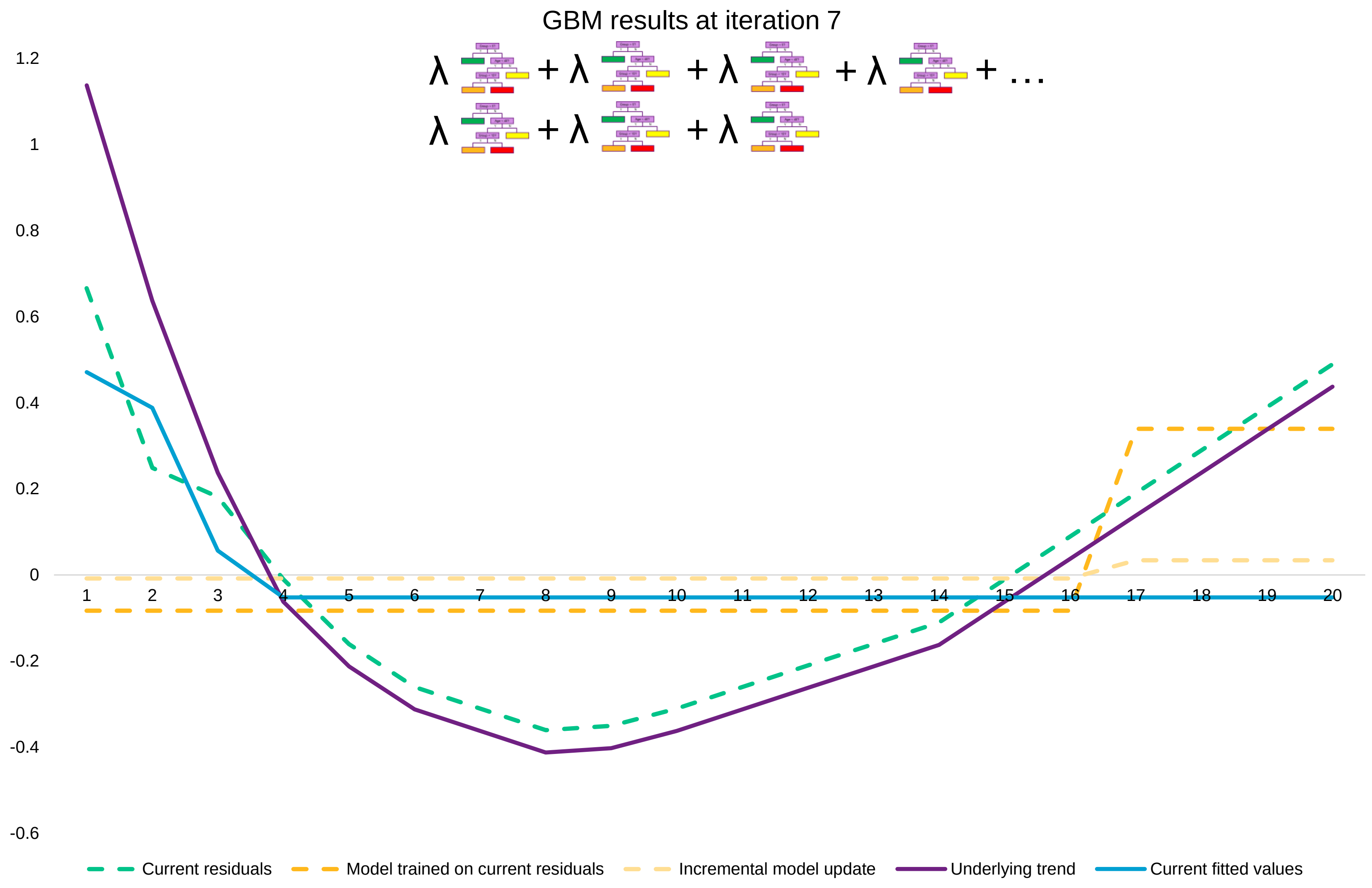

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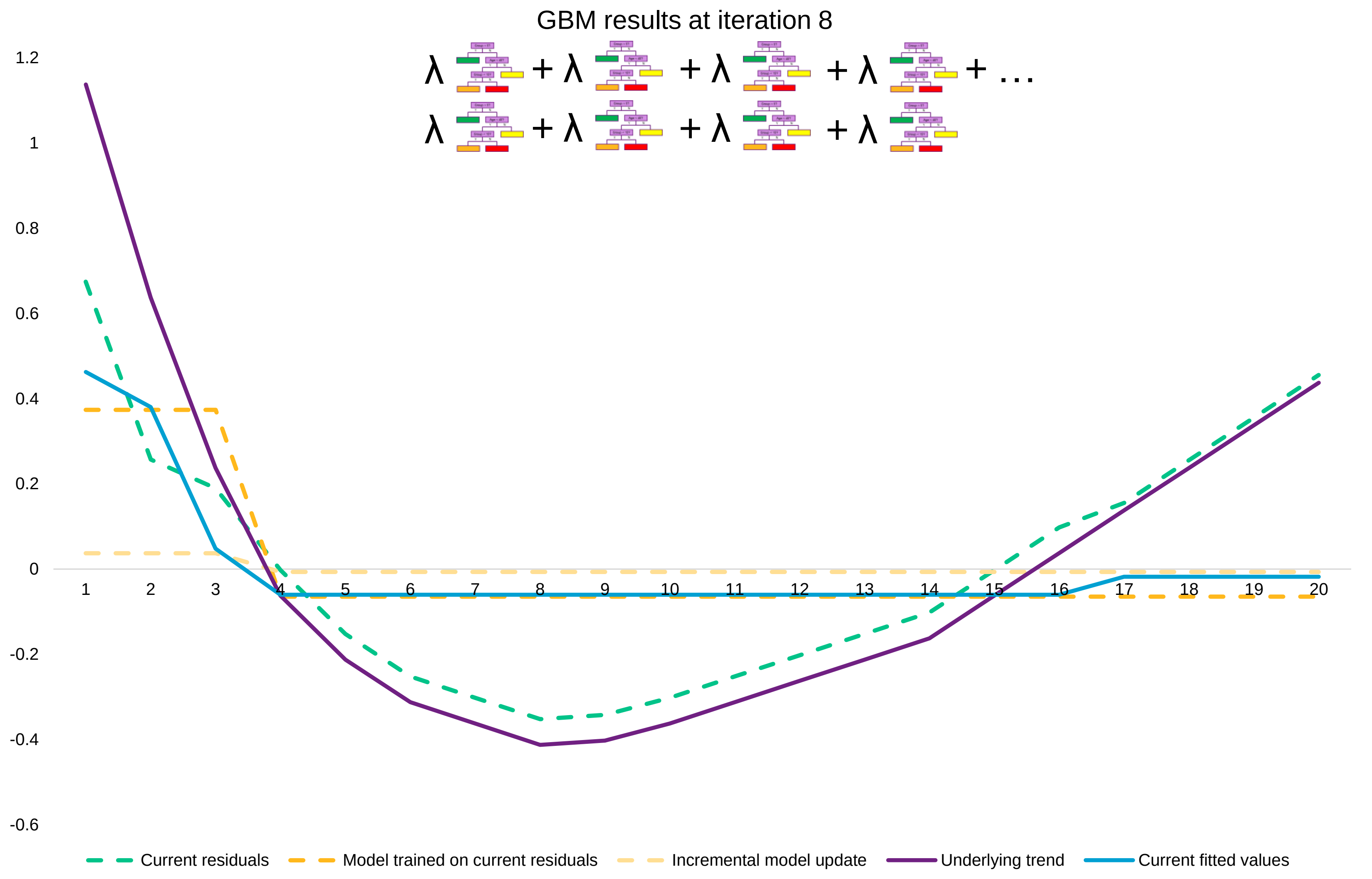
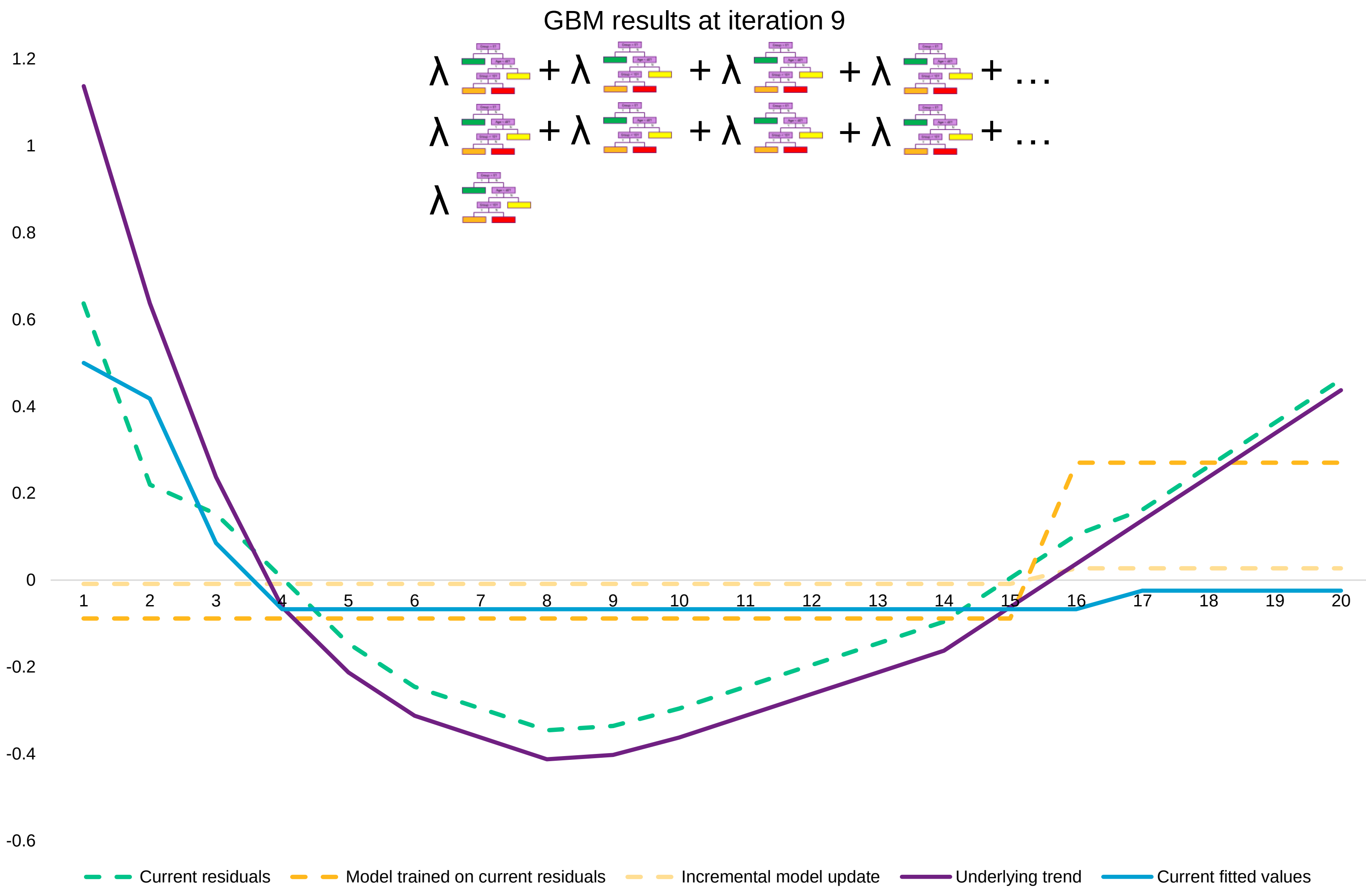
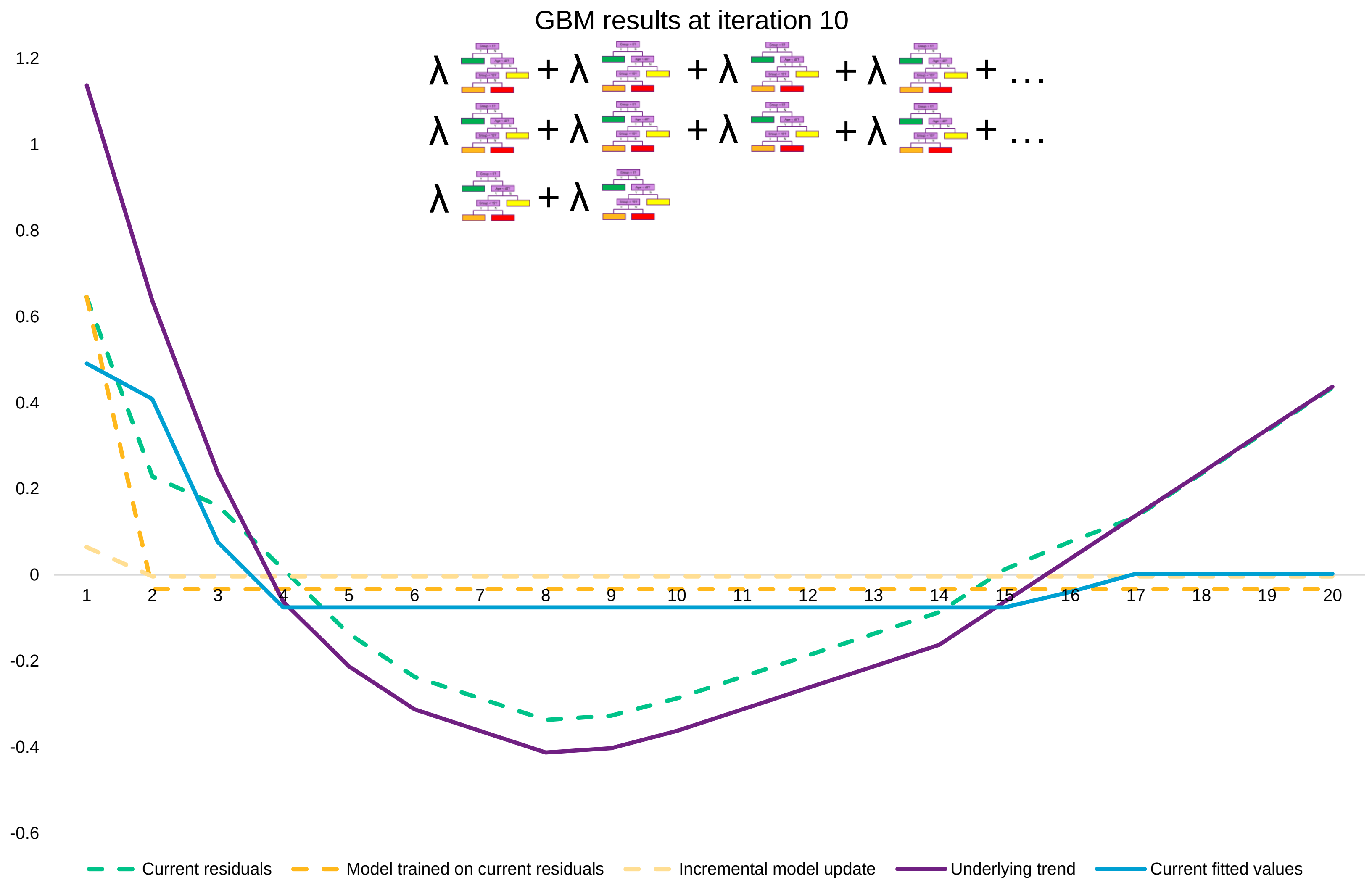


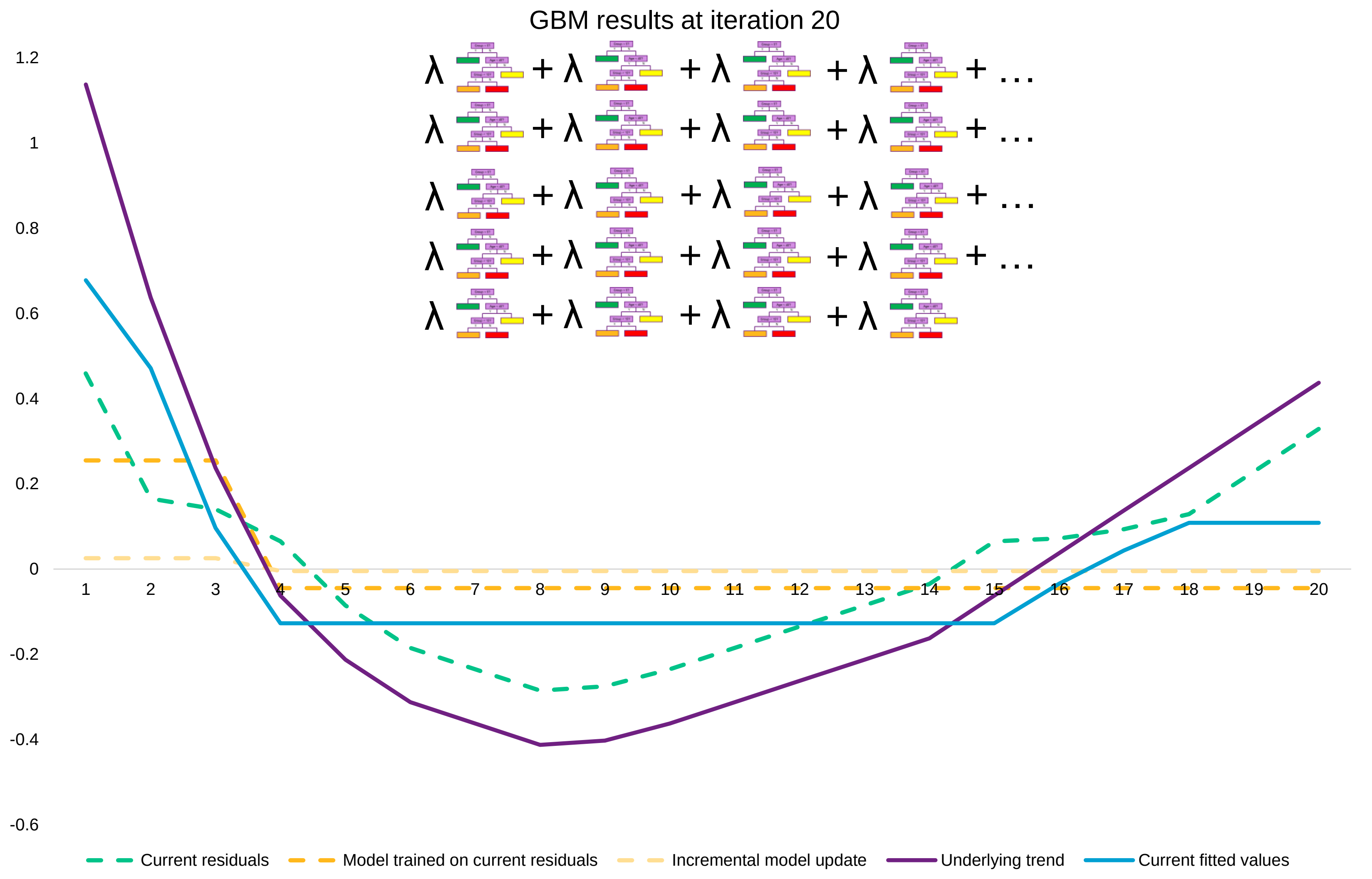
A simple GBM example



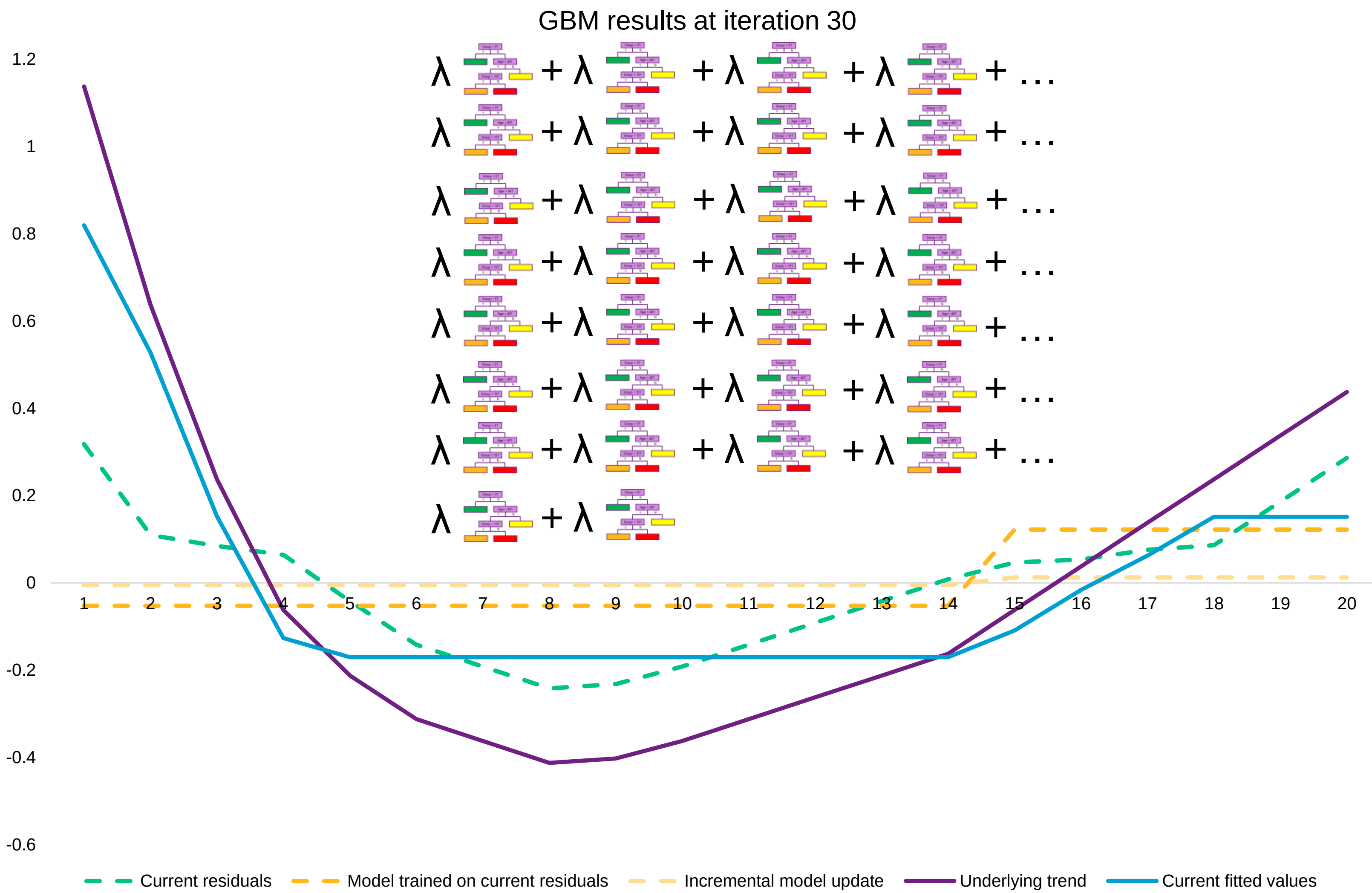
A simple GBM example



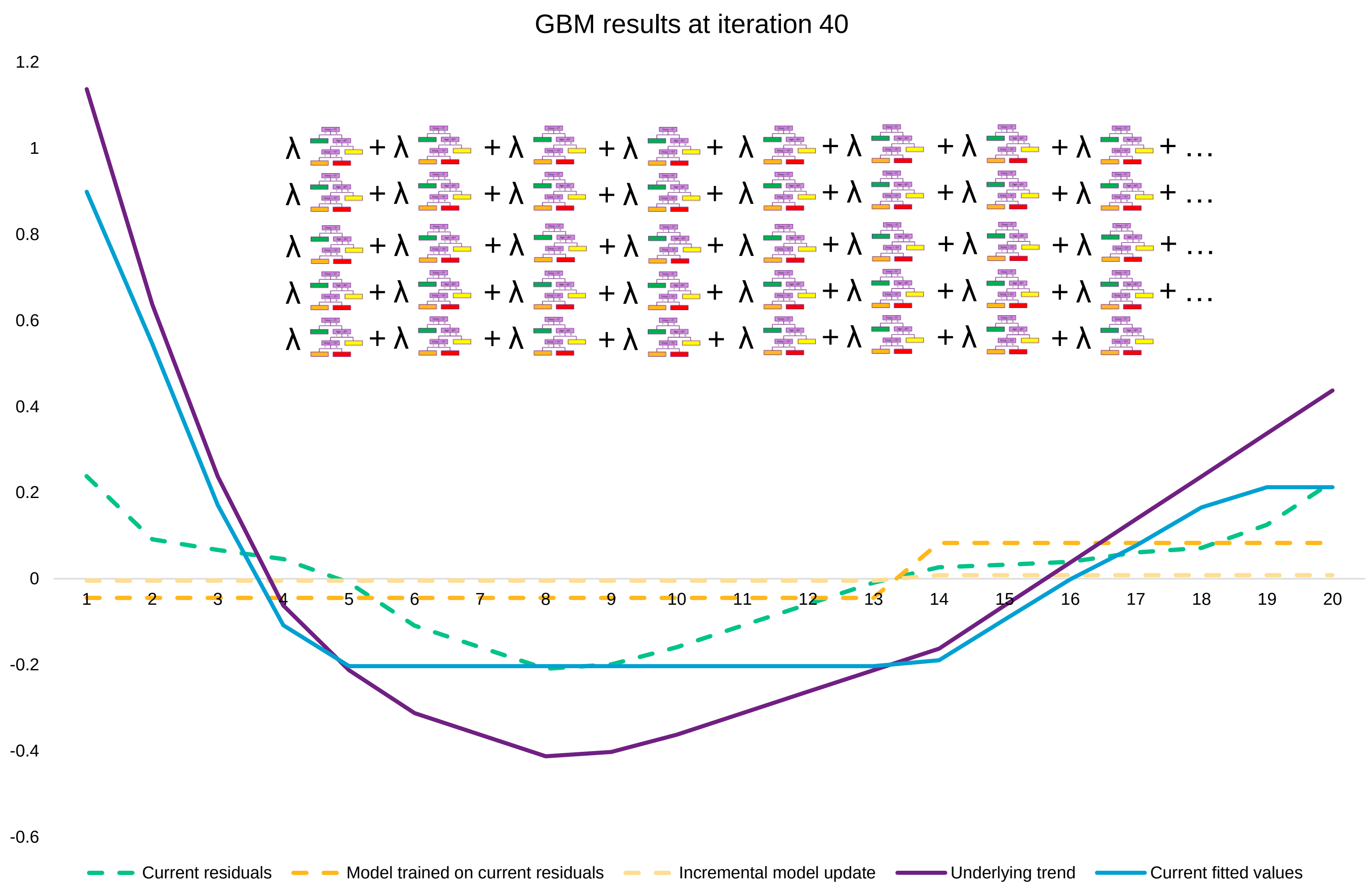
A simple GBM example



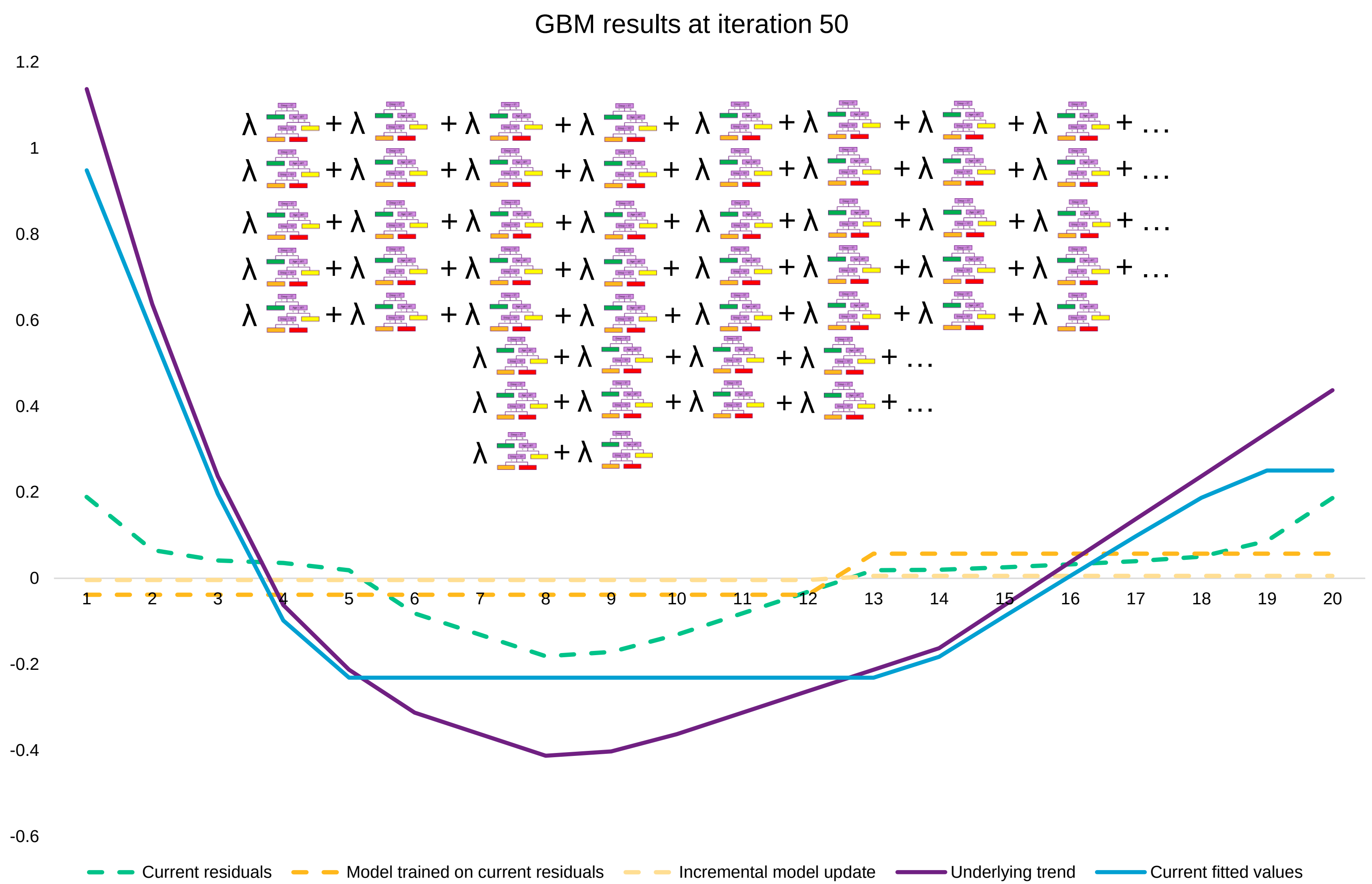
A simple GBM example



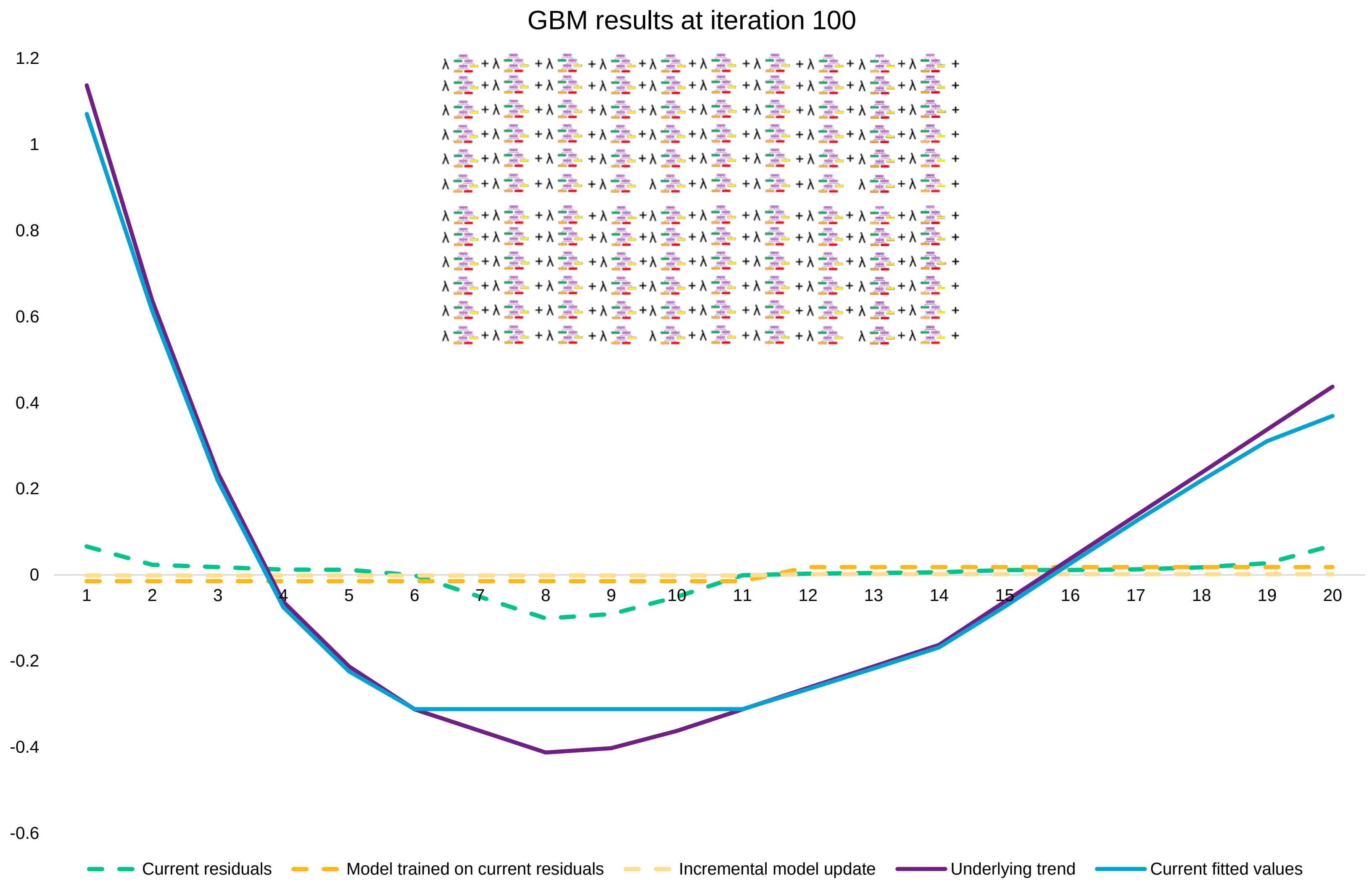
A simple GBM example



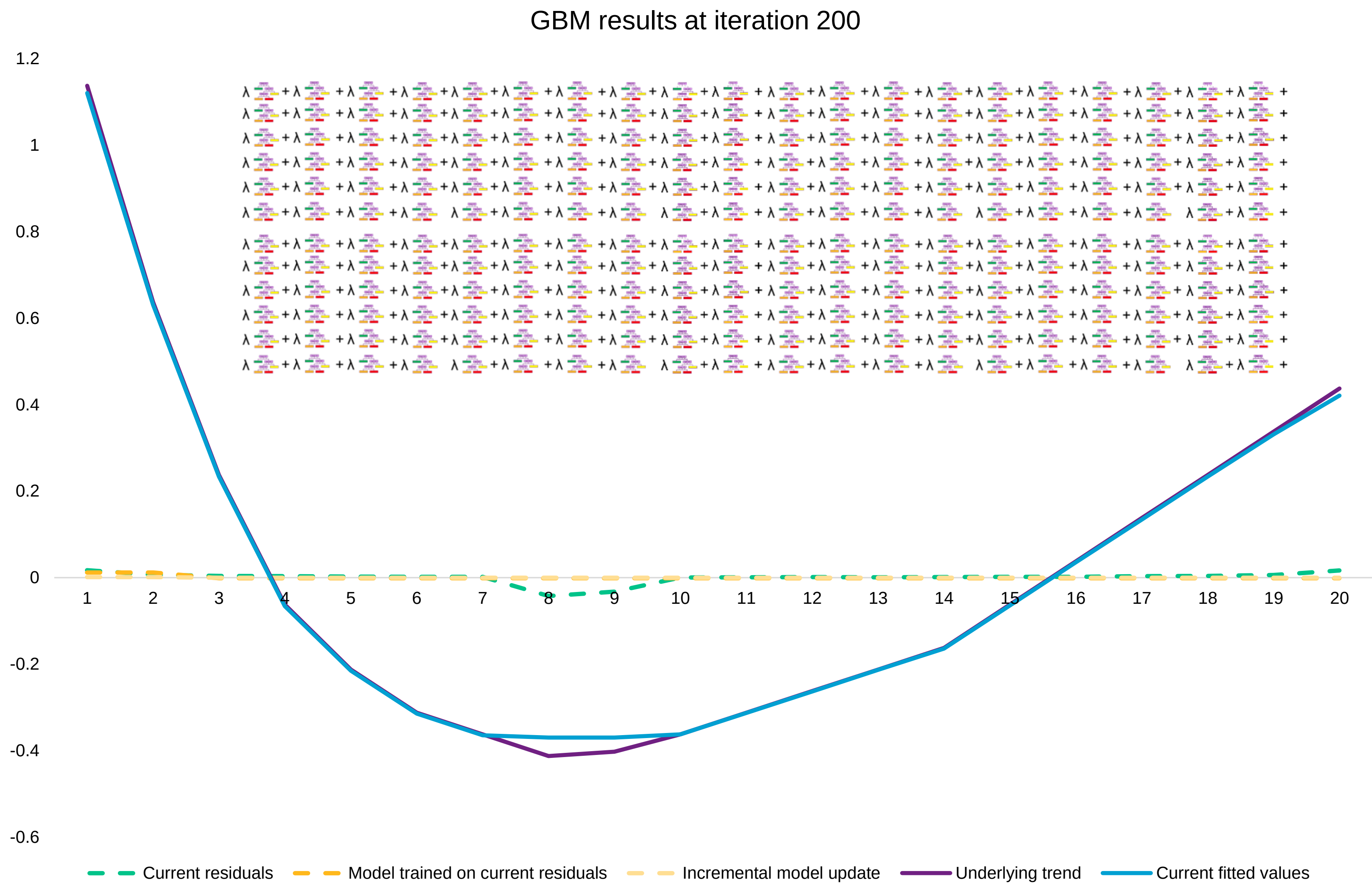
A simple GBM example



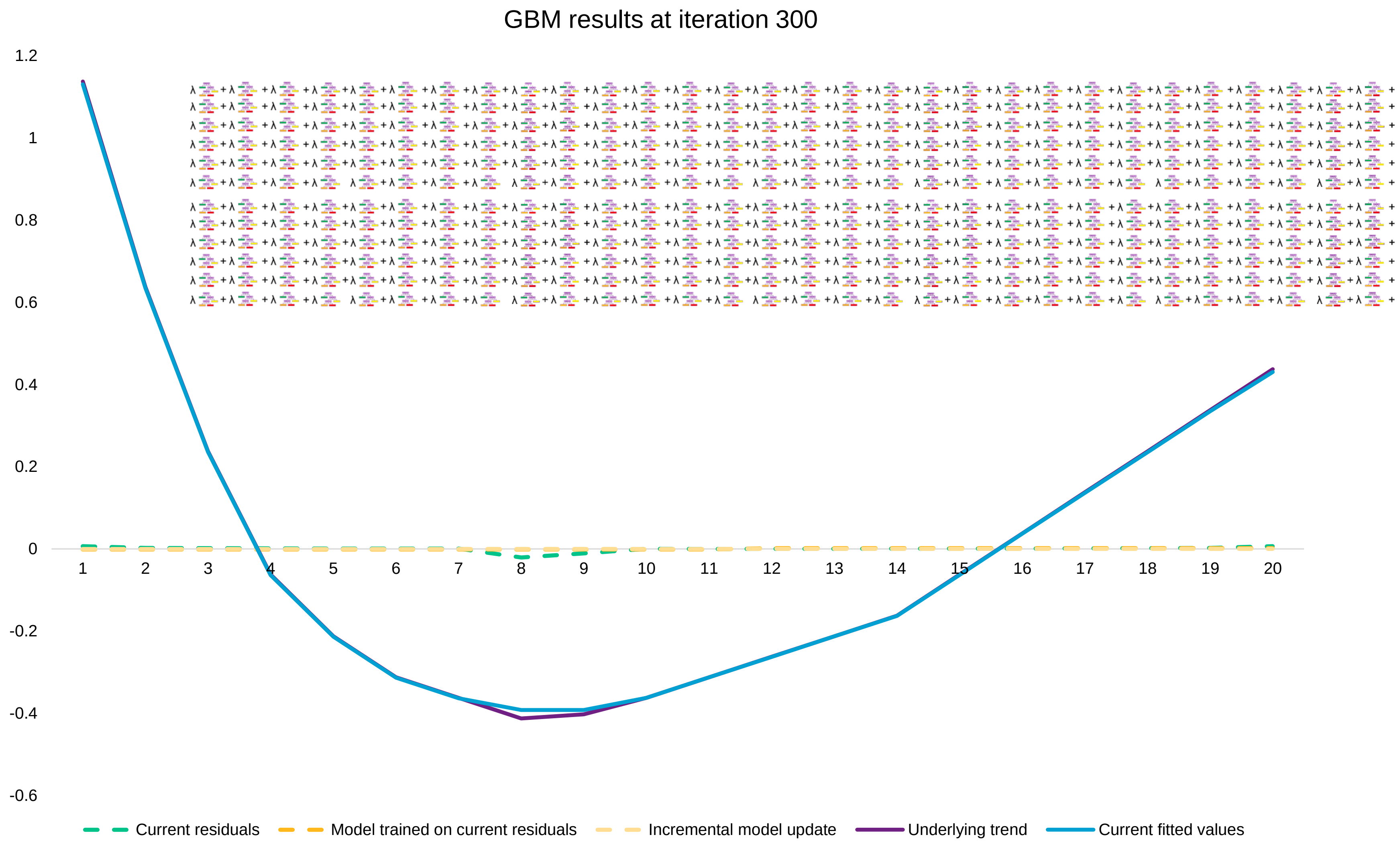
A simple GBM example



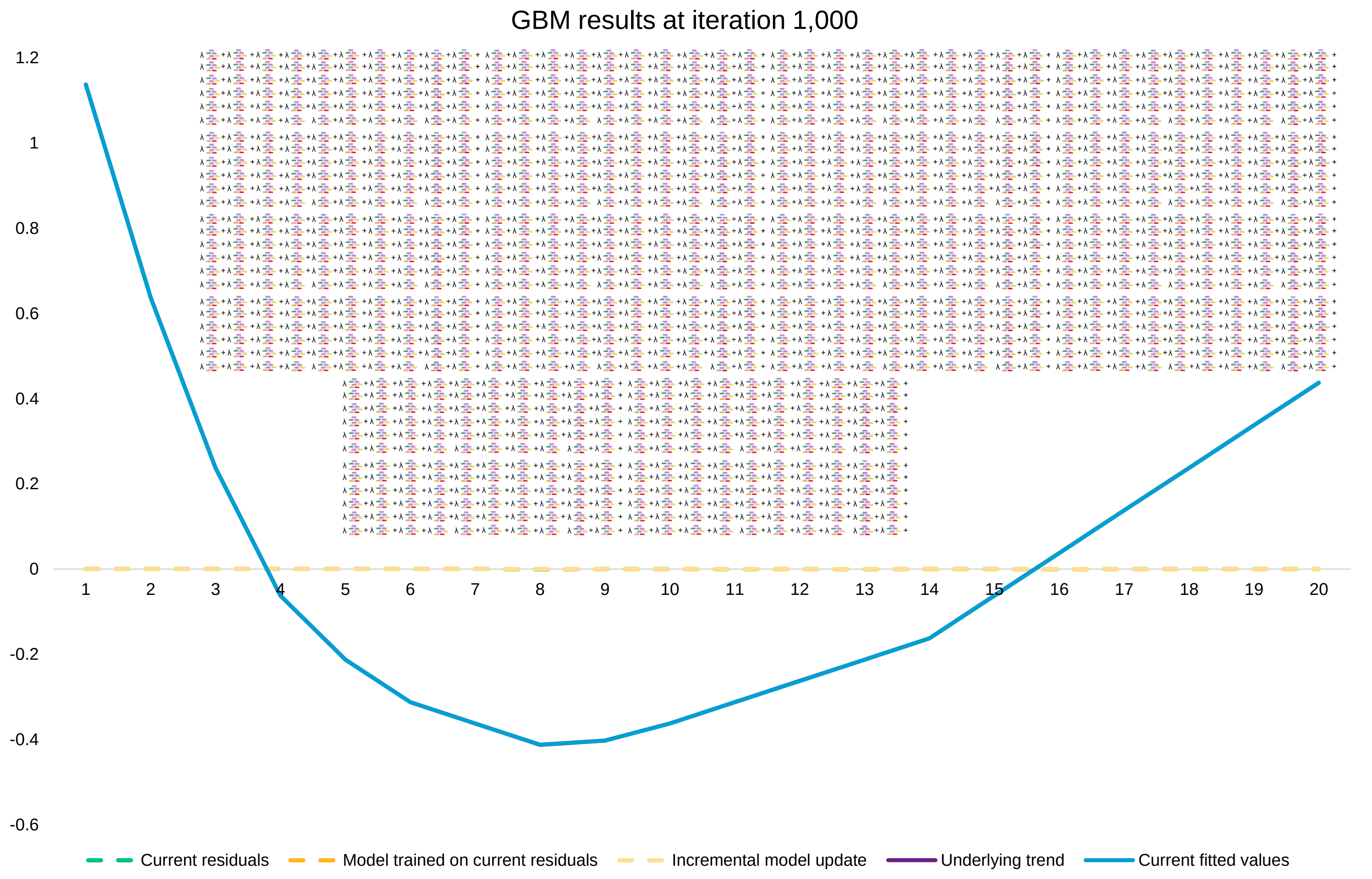
A simple GBM example



A simple GBM example

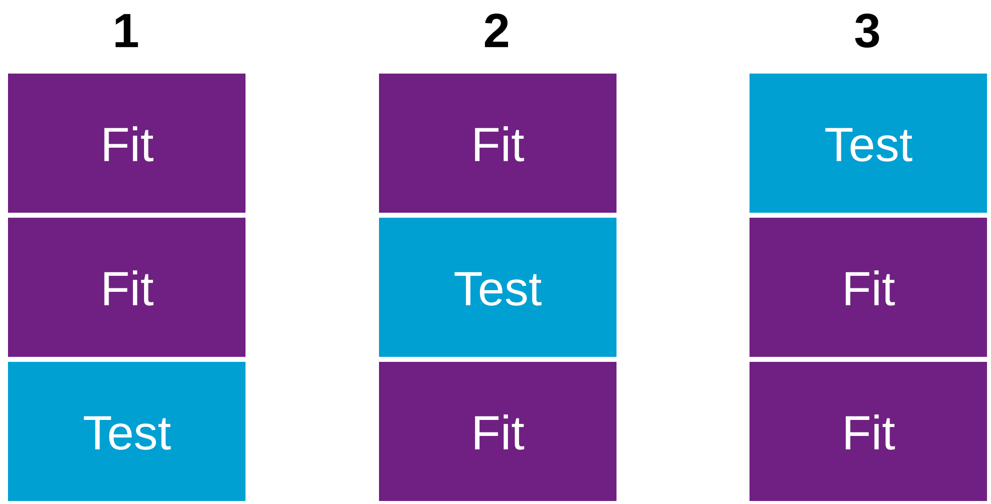


A simple GBM example



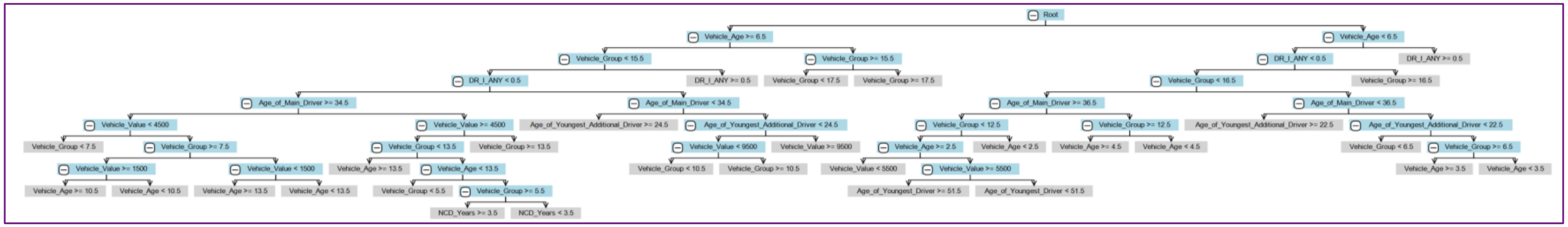
Calibrating the assumptions

- *n*-fold cross validation used to develop the interaction depth and learning rate assumptions
  - Eg for 3-fold validation, split into 3, fit on purple, test on blue parts, take average

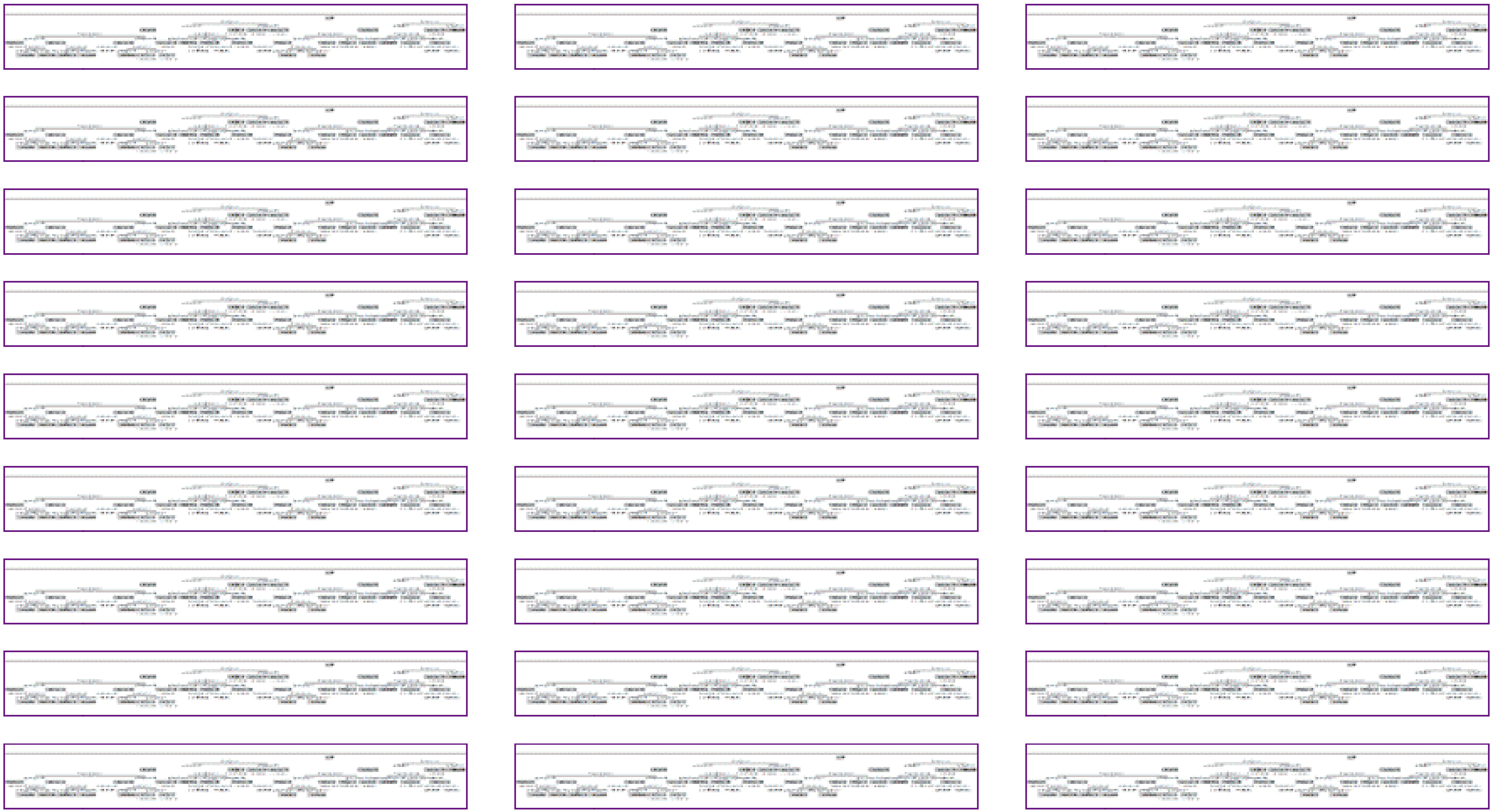


- Resulting plots can be used to determine the optimal assumption choice
  - Including how many trees to run

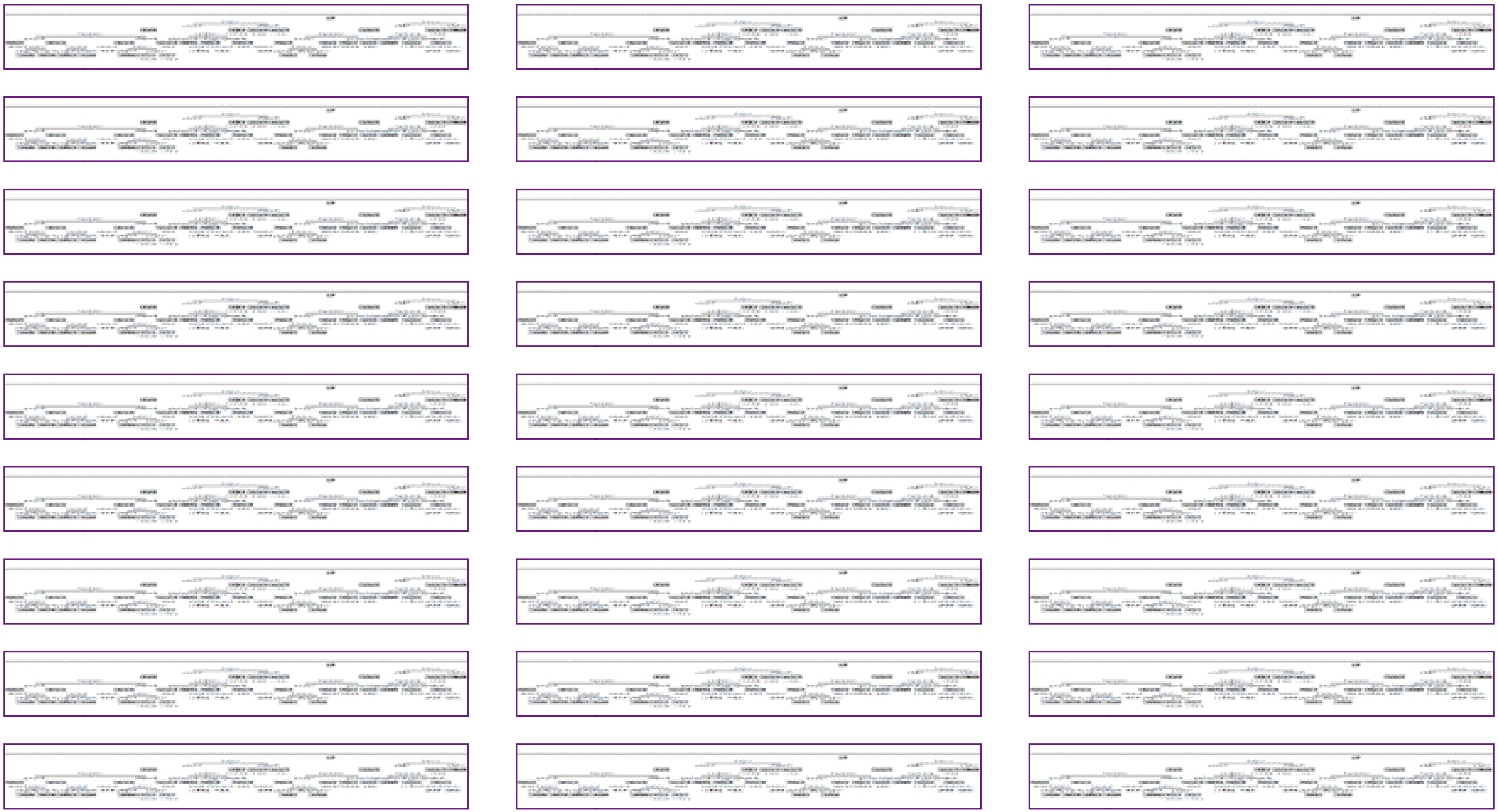
What does a GBM look like?

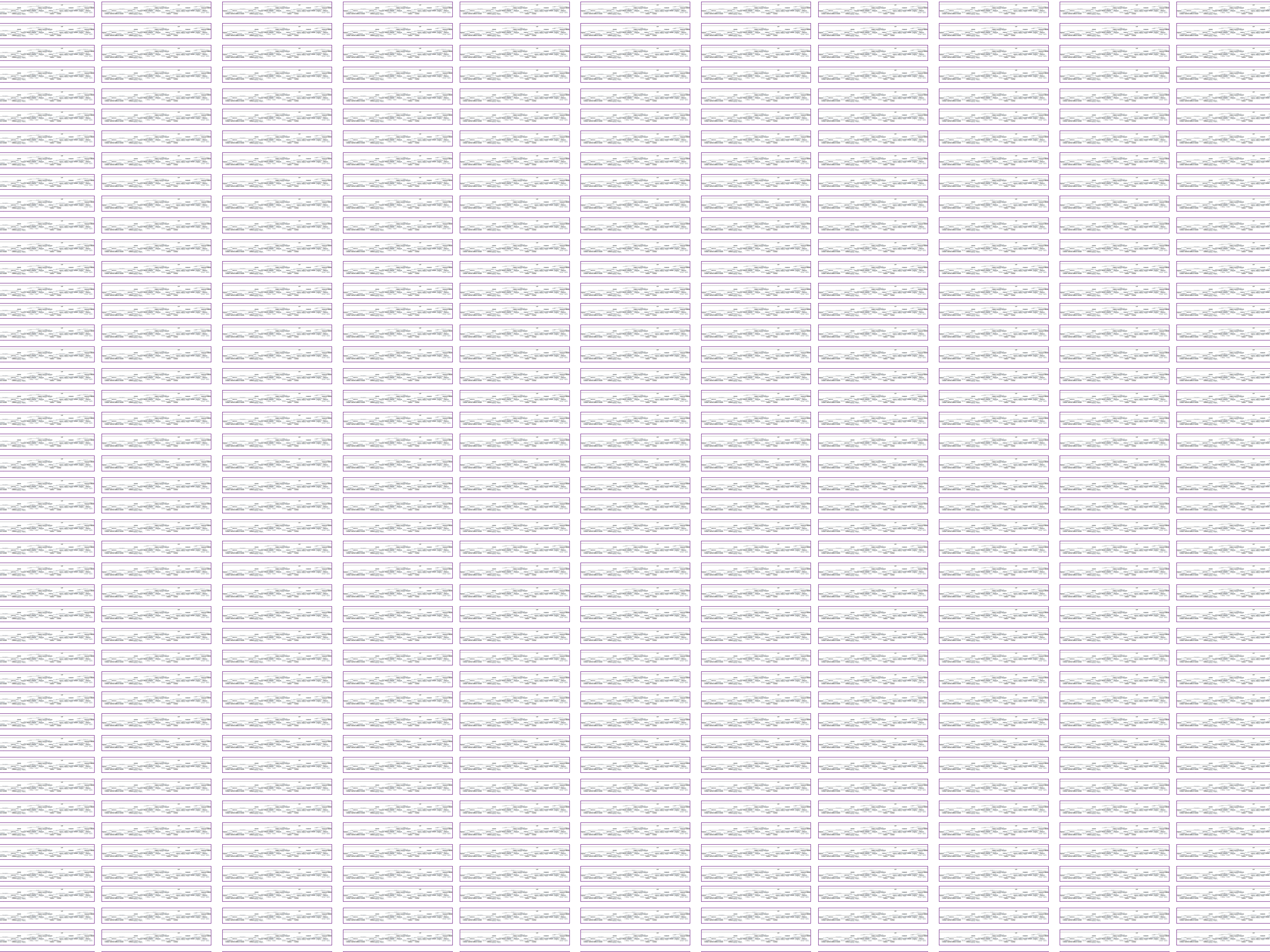


What does a GBM look like?



What does a GBM look like?

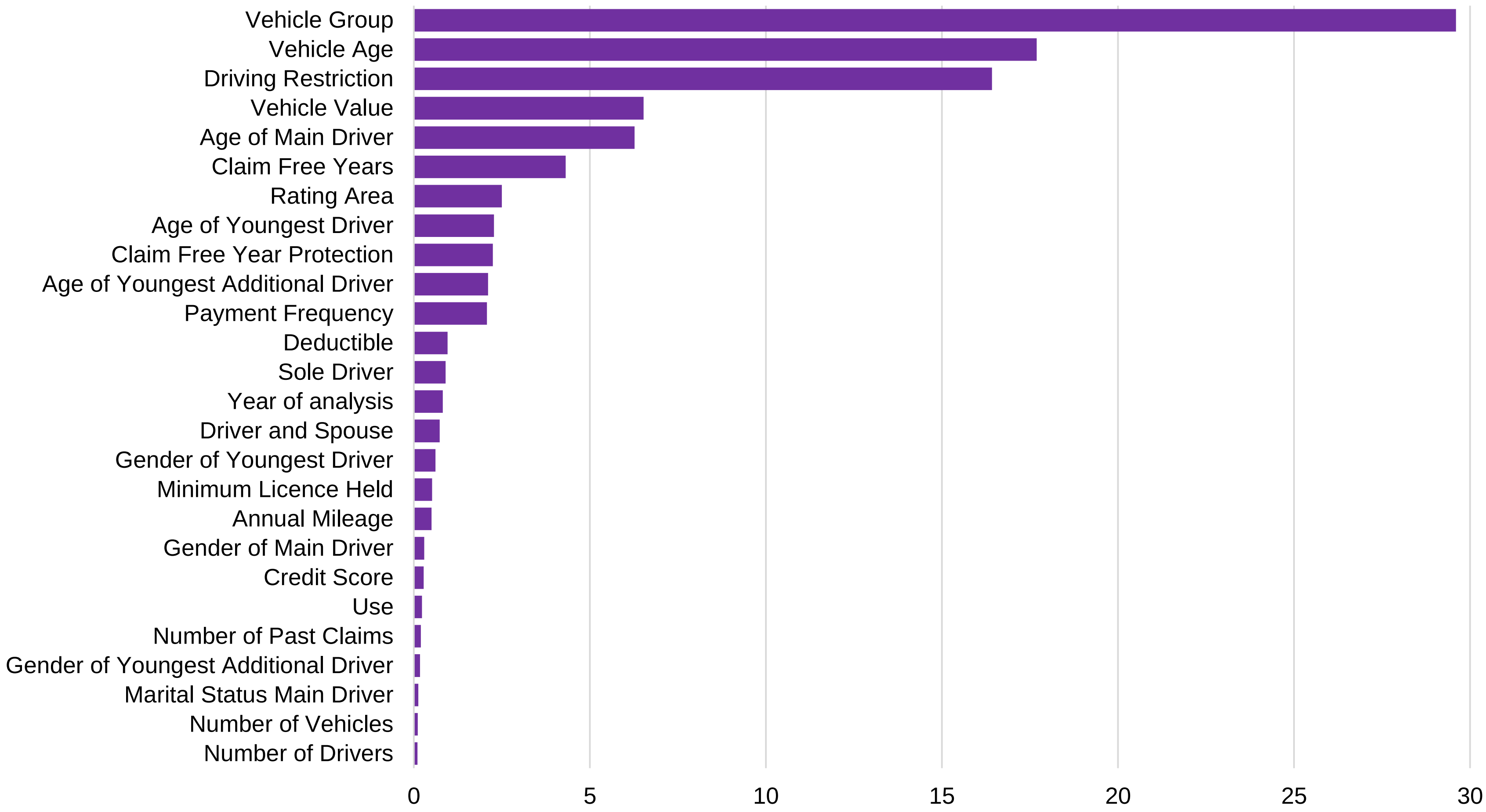




- Does it work?
- How does it work?

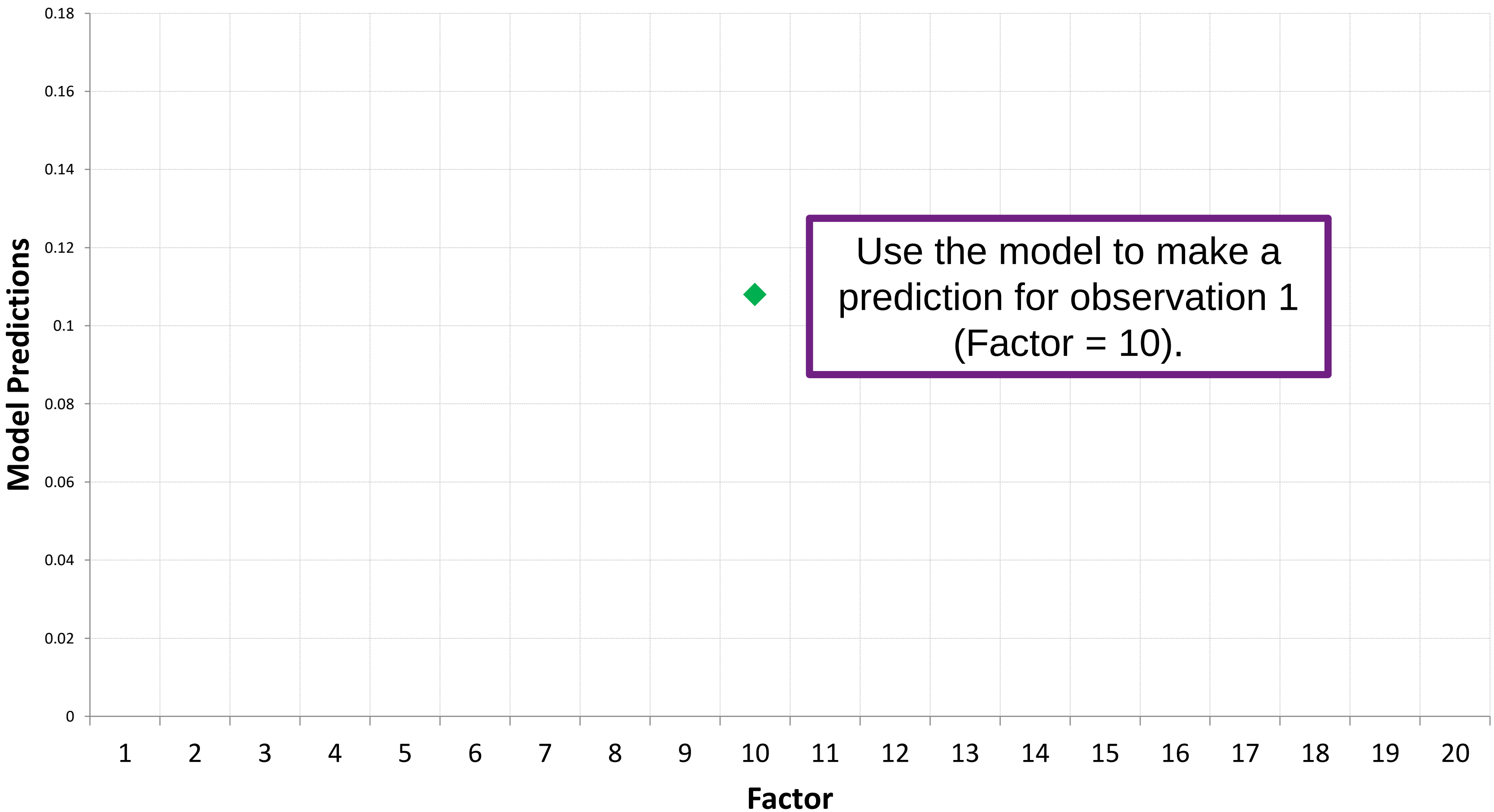
Factor importance – relative influence

The relative influence of a factor can be measured as the total reduction in error attributable to splits by that factor, across all trees in the GBM



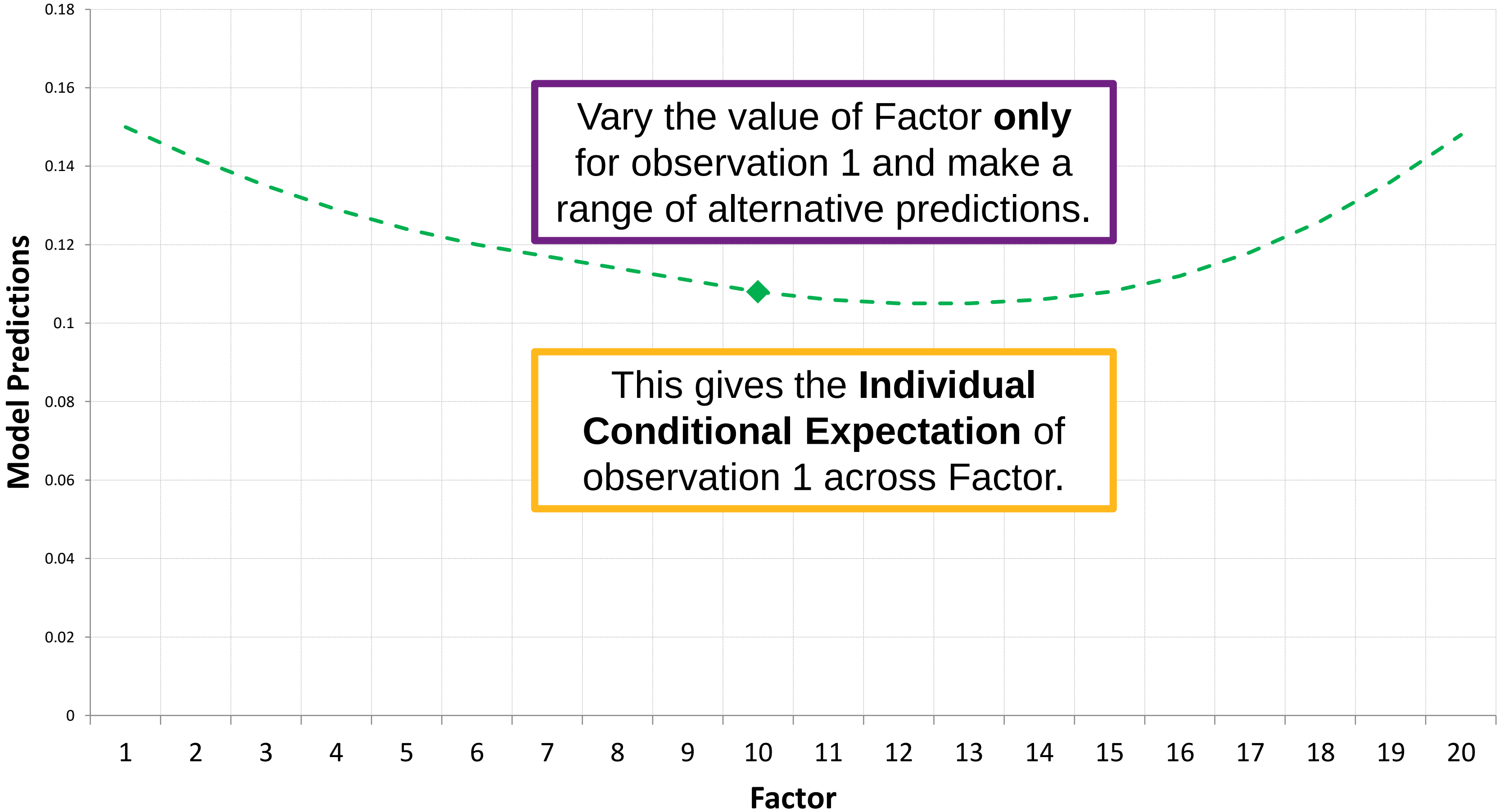
Partial dependency plots

Example



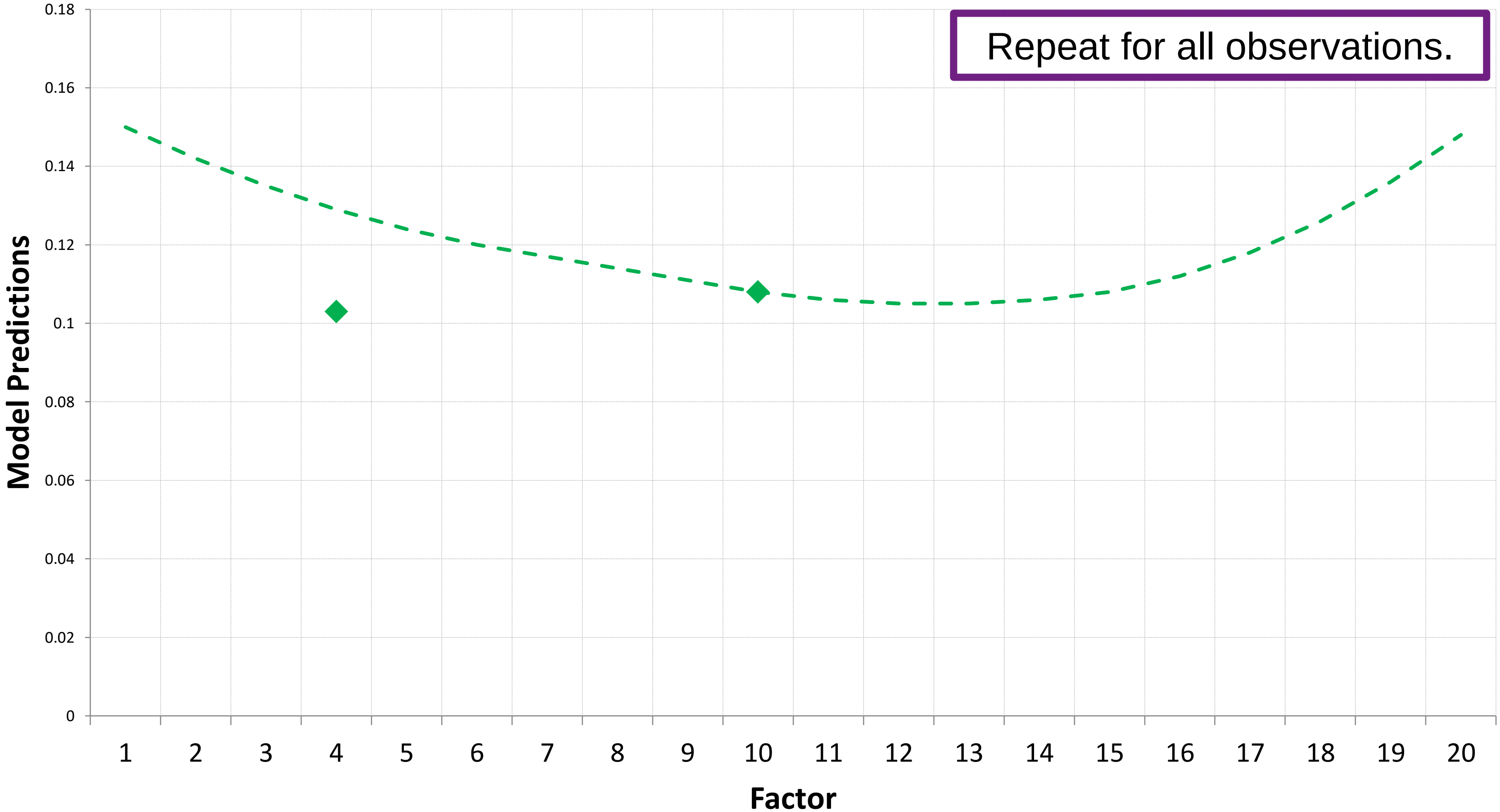
Partial dependency plots

Example



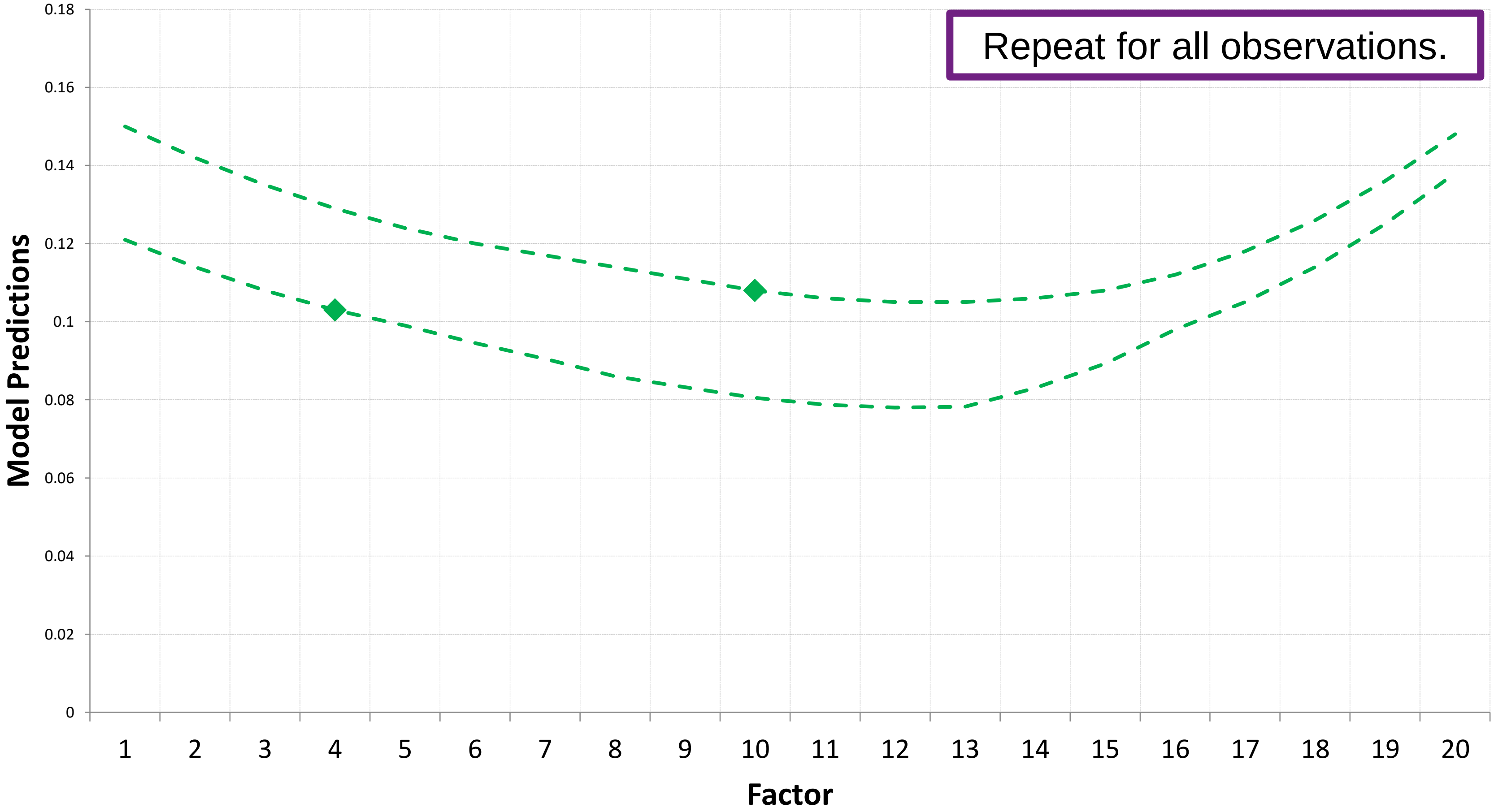
Partial dependency plots

Example



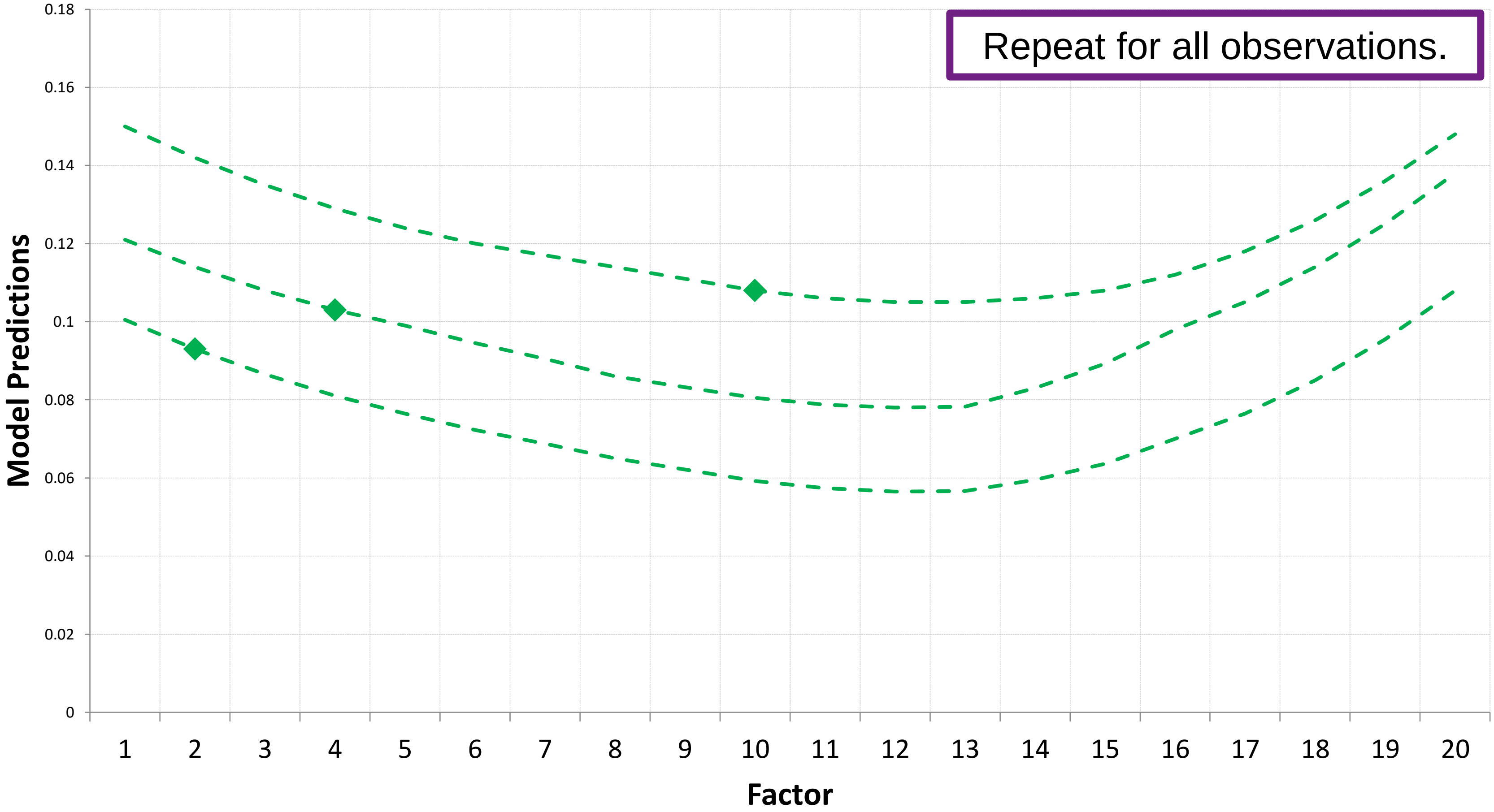
Partial dependency plots

Example



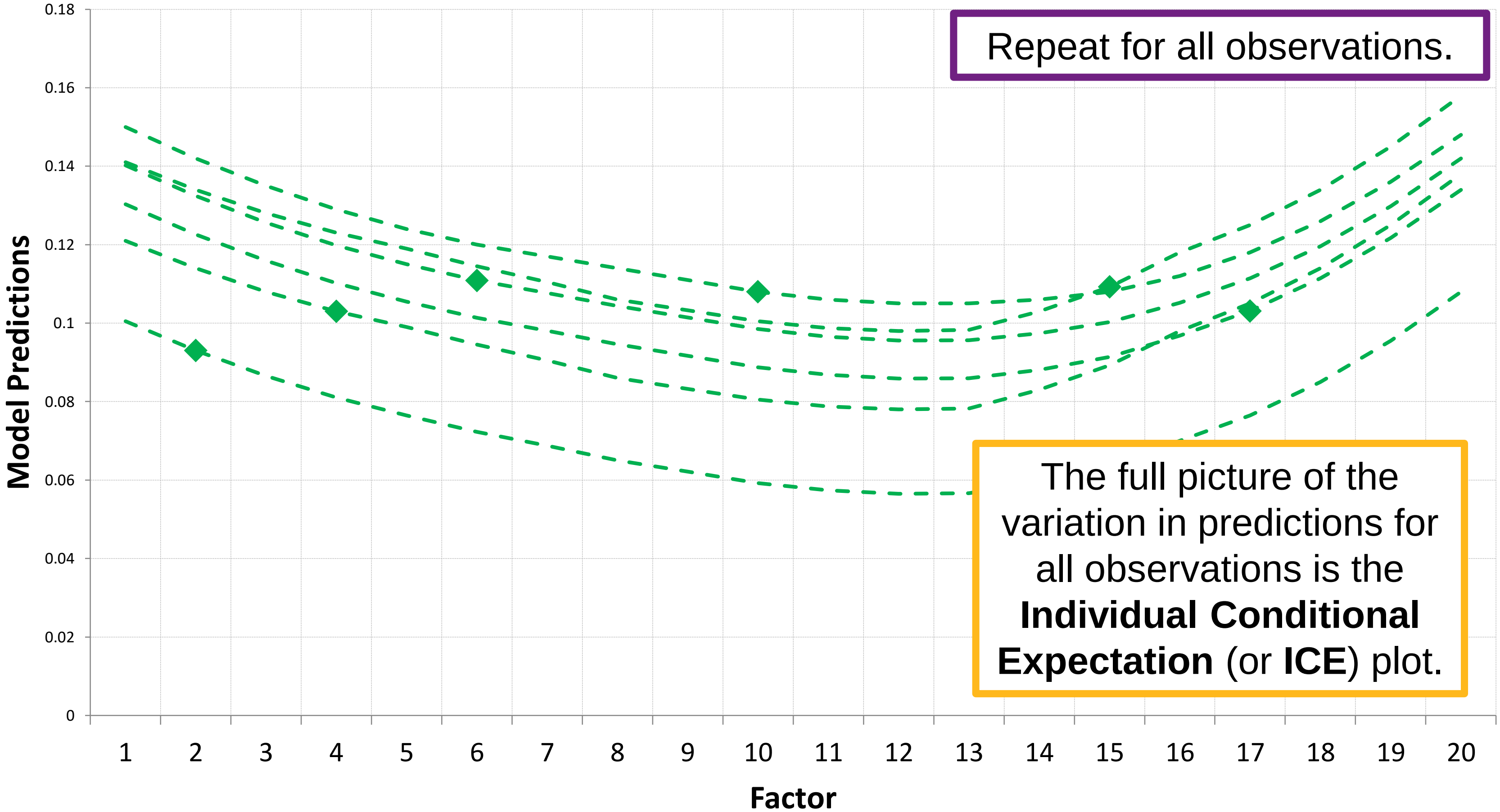
Partial dependency plots

Example



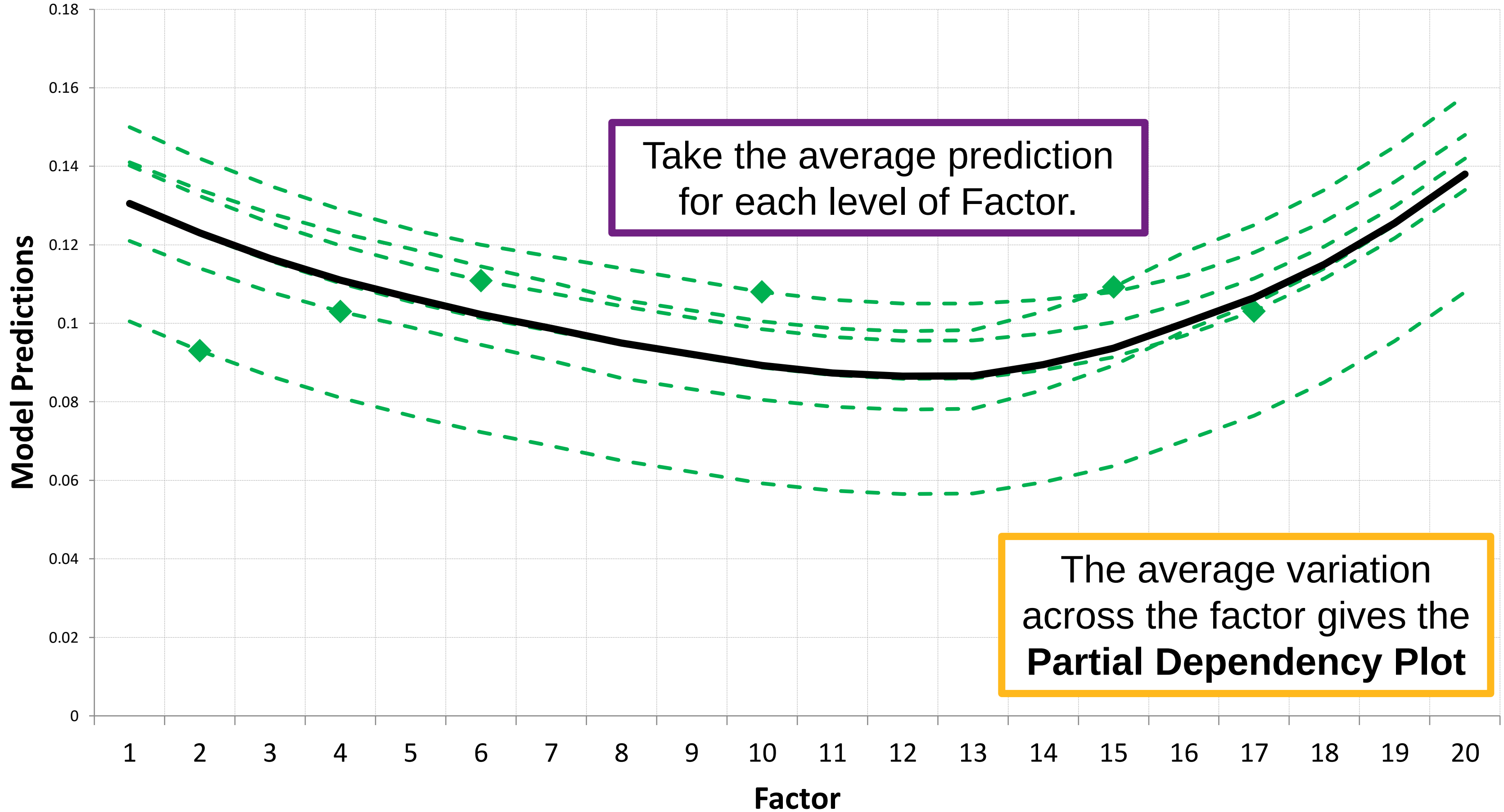
Partial dependency plots

Example



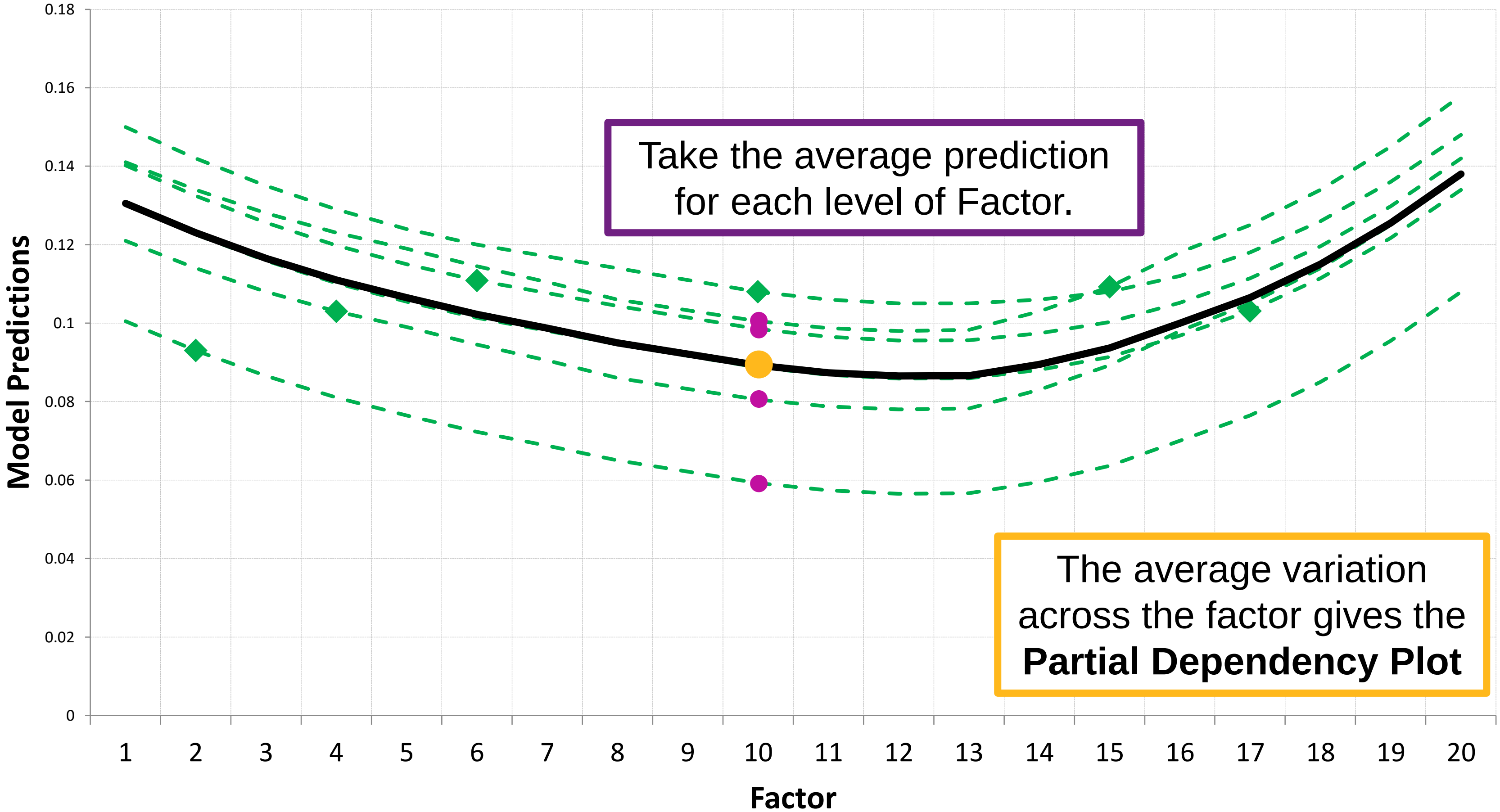
Partial dependency plots

Example



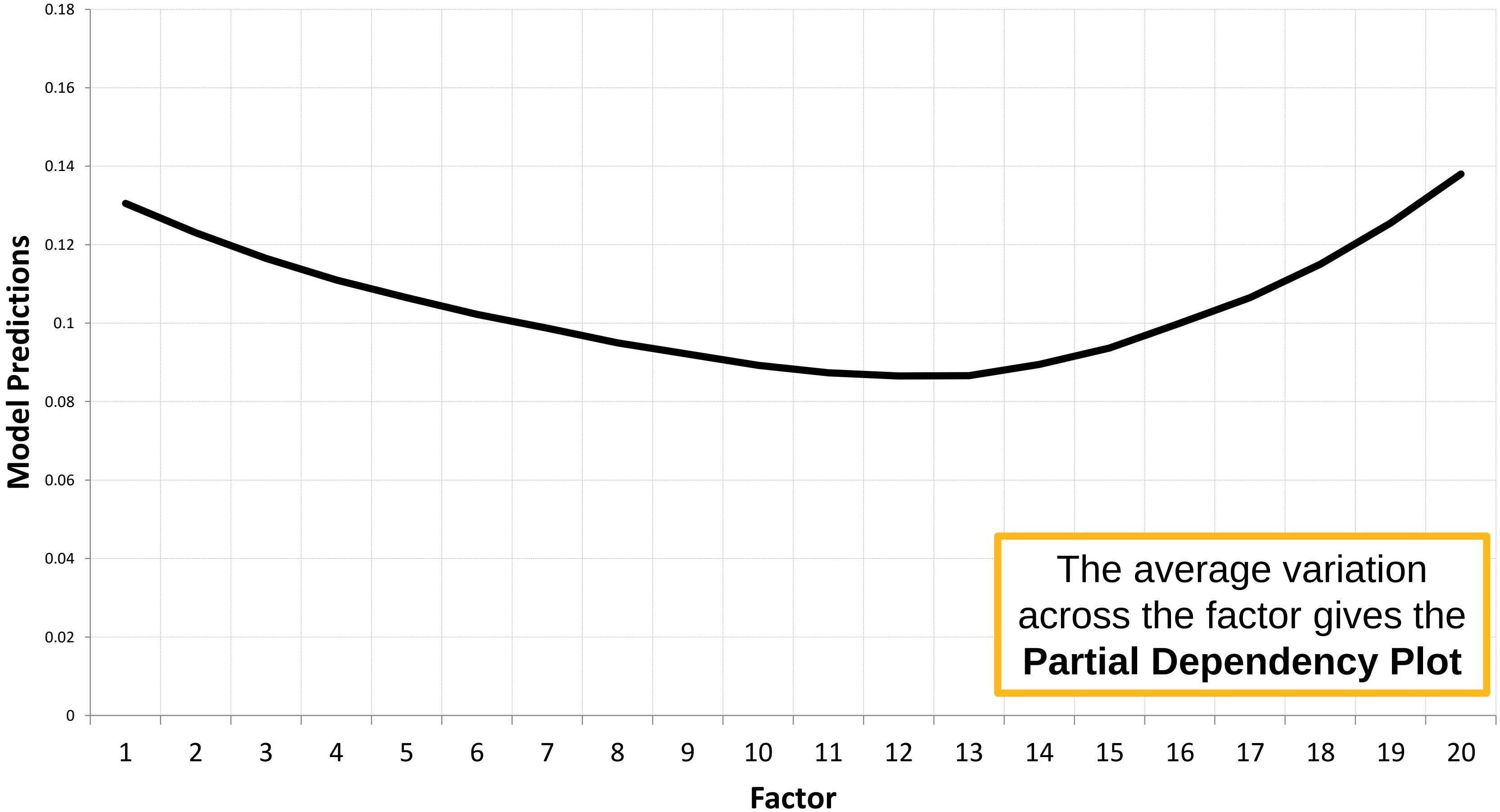
Partial dependency plots

Example



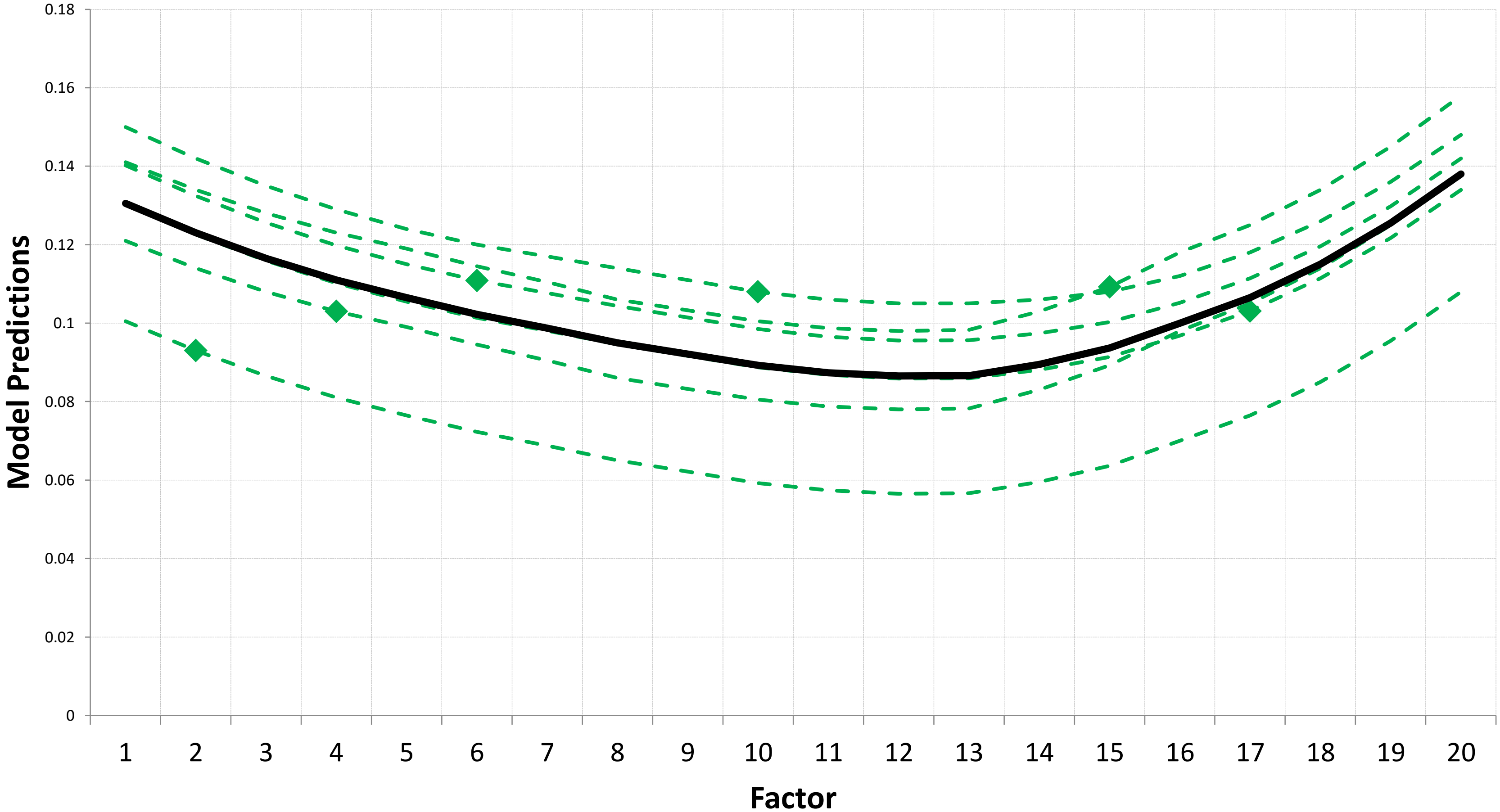
Partial dependency plots

Example



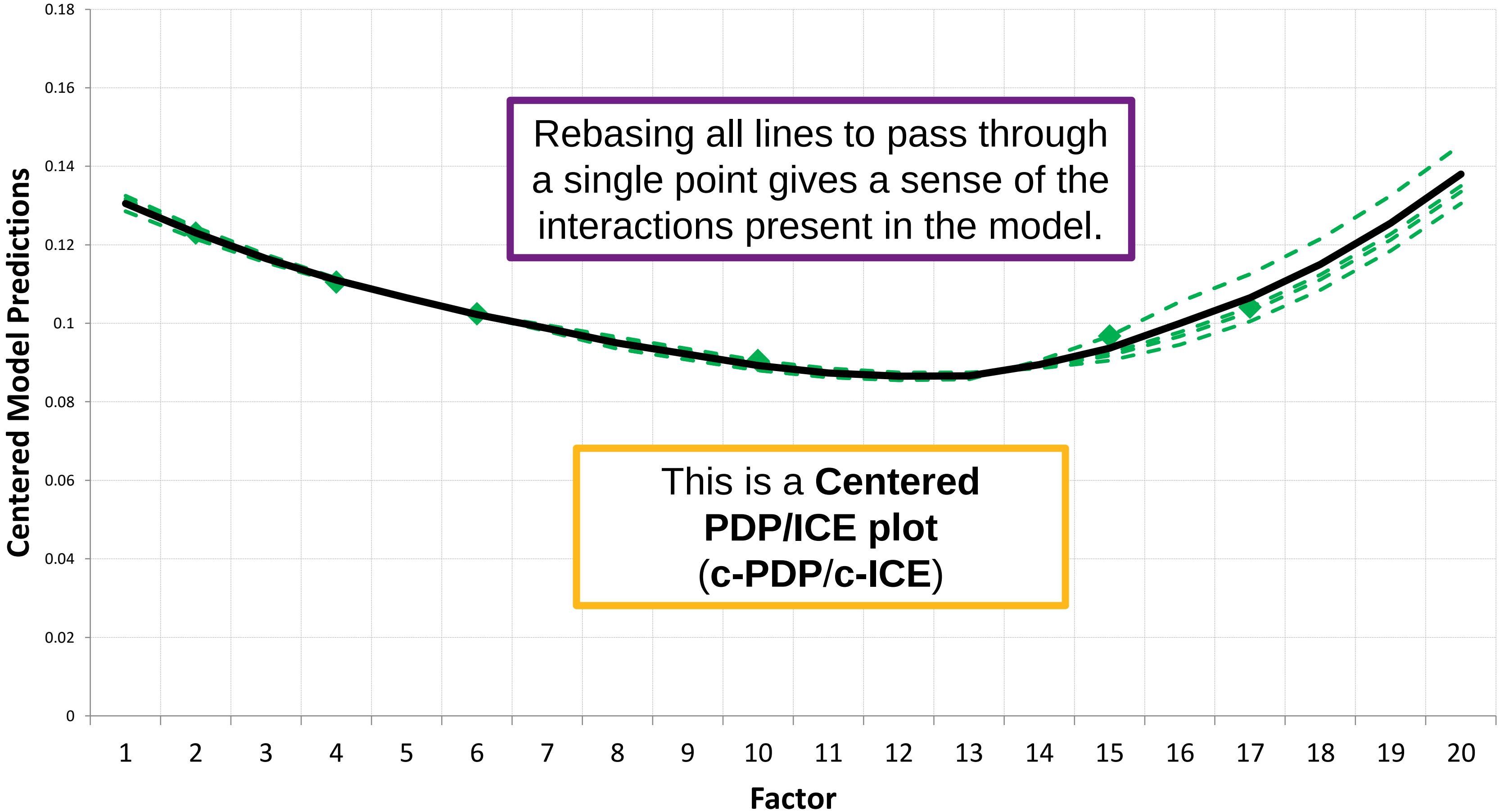
Partial dependency plots

Example



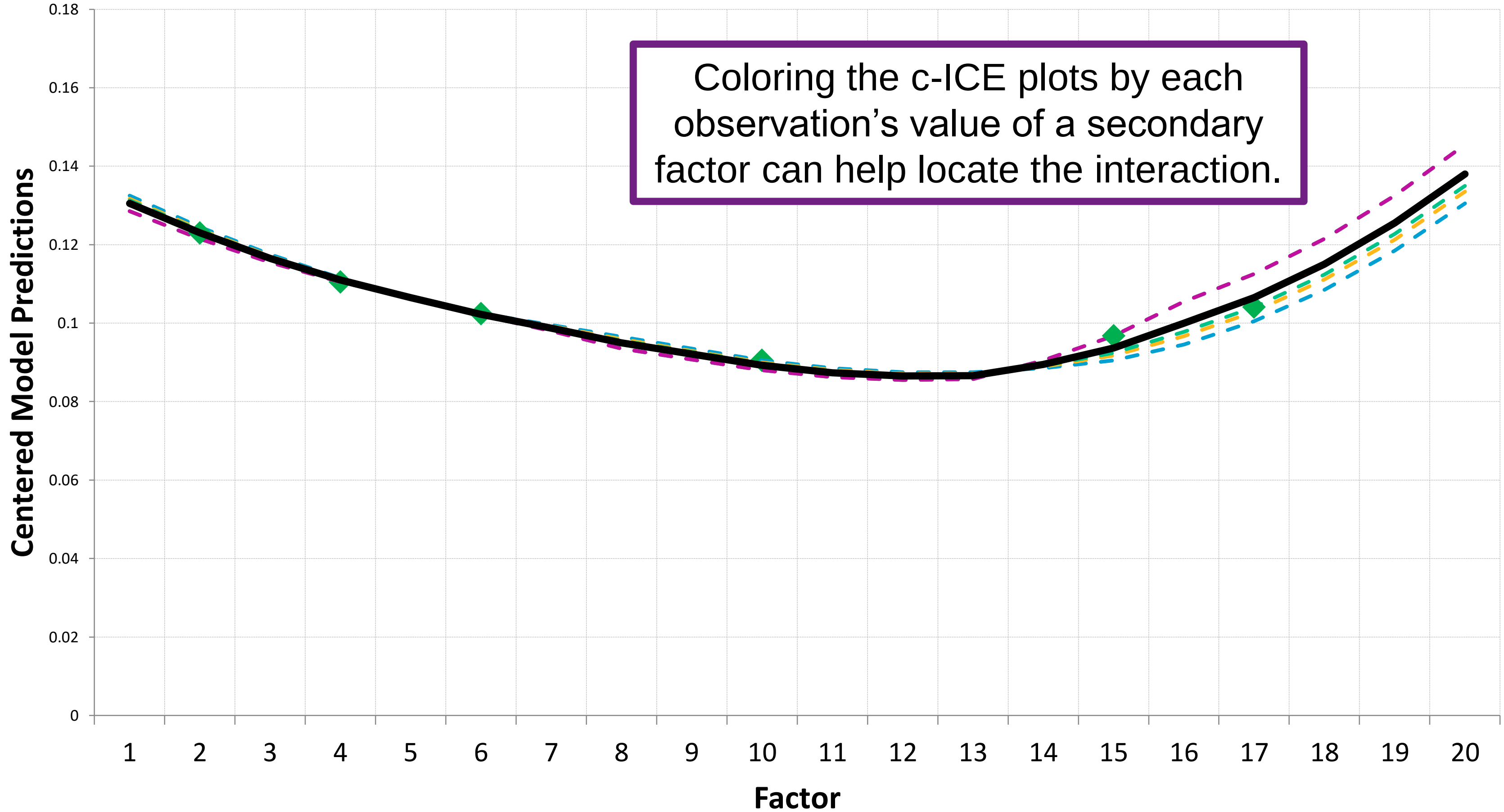
Partial dependency plots

Example

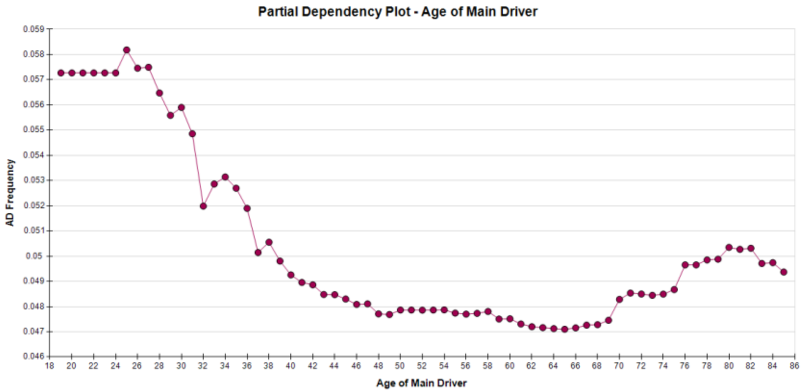


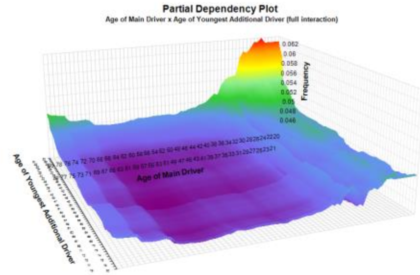
Partial dependency plots

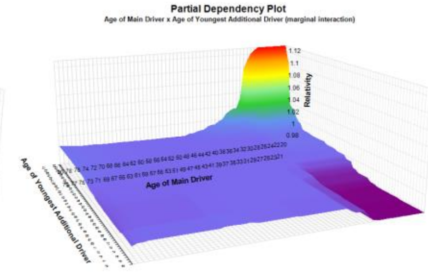
Example

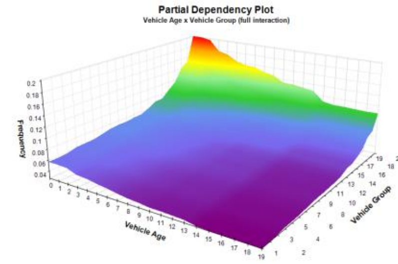


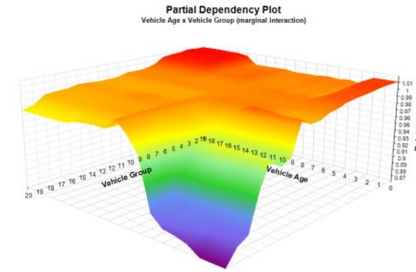
Partial dependency plots etc

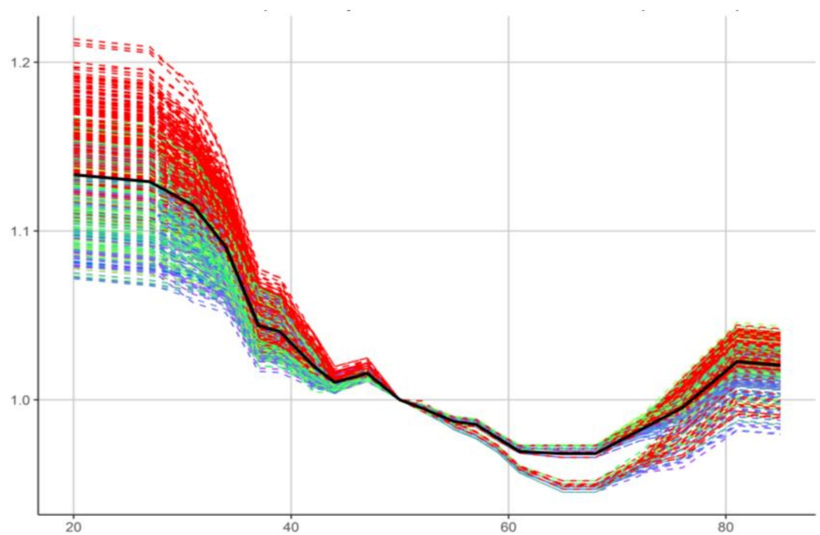


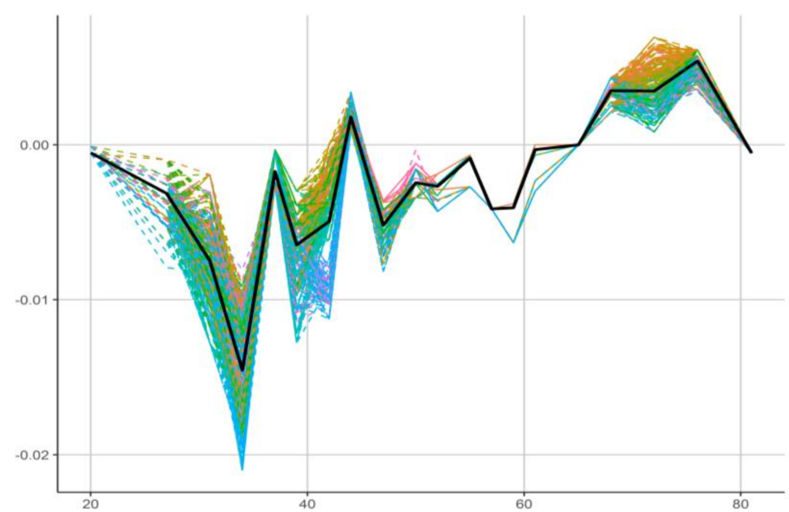




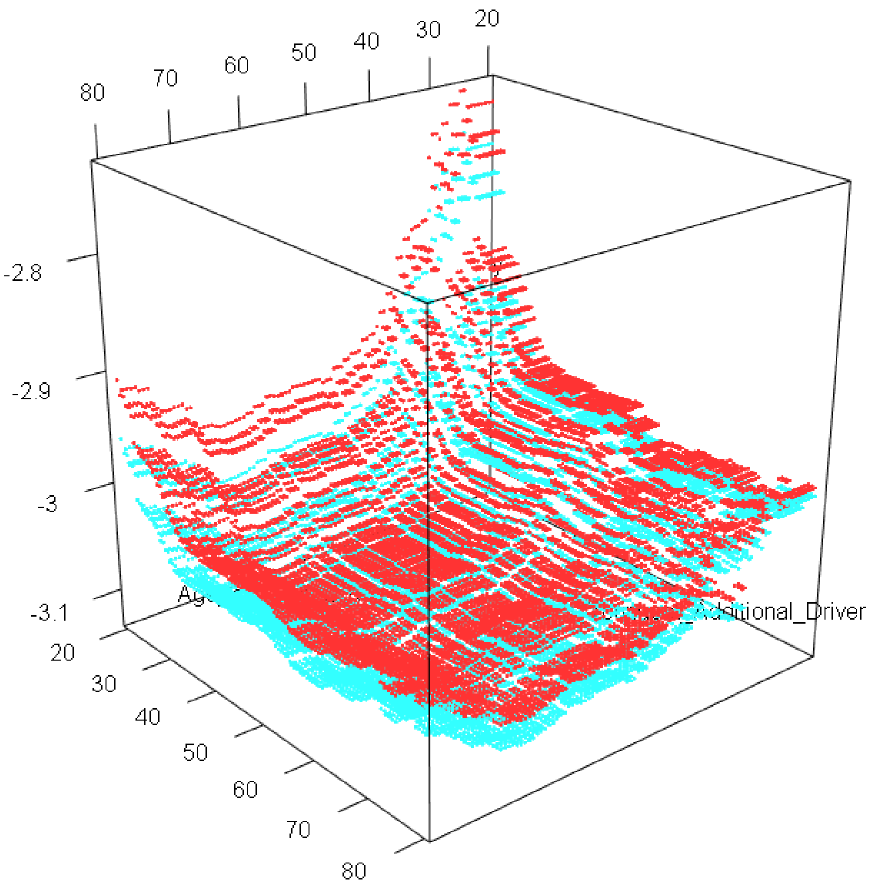








Partial dependency plots



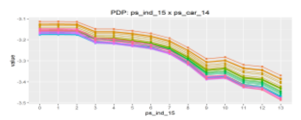
Advantages

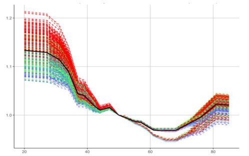
- Qualitative description of properties of relationships
- Most revealing of additive and multiplicative relationships

Disadvantages

- "GLM view of a non-GLM thing"
- Interaction effects outside of the chosen subset may be obfuscated
- eg if X_1X_2 is important and X_2 is averaged out in the partial dependence plot, X_1 may show as being heterogeneous, thus obfuscating the complexity of the modelled relationships

So what?

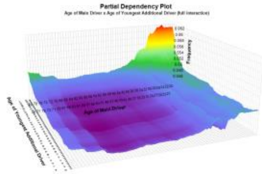




	Age	Exposure	Burning Cost
1	<=20	1,720	179
2	21-30	34,893	122
3	31-50	118,182	102
4	51+	127,054	70
5	Age Total	281,849	91

	Vehicle Group	Exposure	Burning Cost
1	1-10	164,107	77
2	11-14	84,859	101
3	15-18	28,952	116
4	19-20	3,931	272
5	VG Total	281,849	91

	Gender	Exposure	Burning Cost
1	Male	197,339	92
2	Female	84,510	87
3	Gender Total	281,849	91



Deploying GBMs

Model down into multiplicative tables via GLMs

	Age	Exposure	Burning Cost
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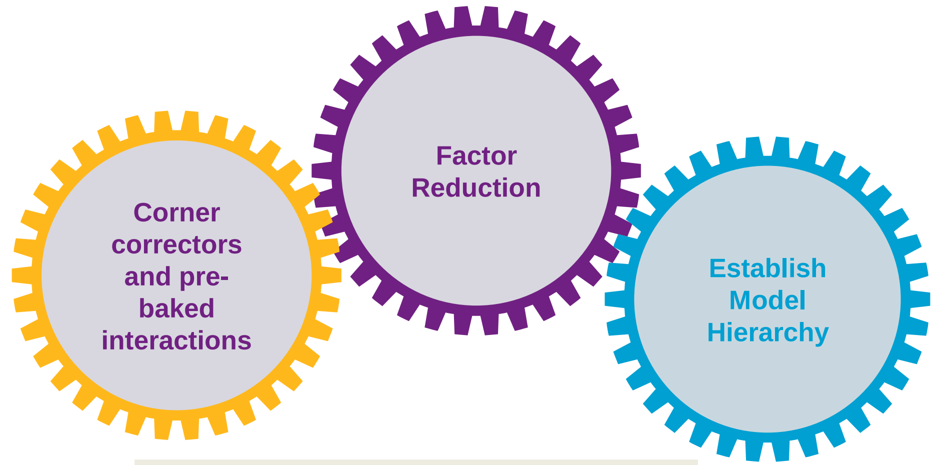


Use insights to guide GLM

Analytical environ-ment

Next gen rating engine

Main Policy Admin System

Deploy directly

Deploying GBMs

Pre / post mapping

Data

Model

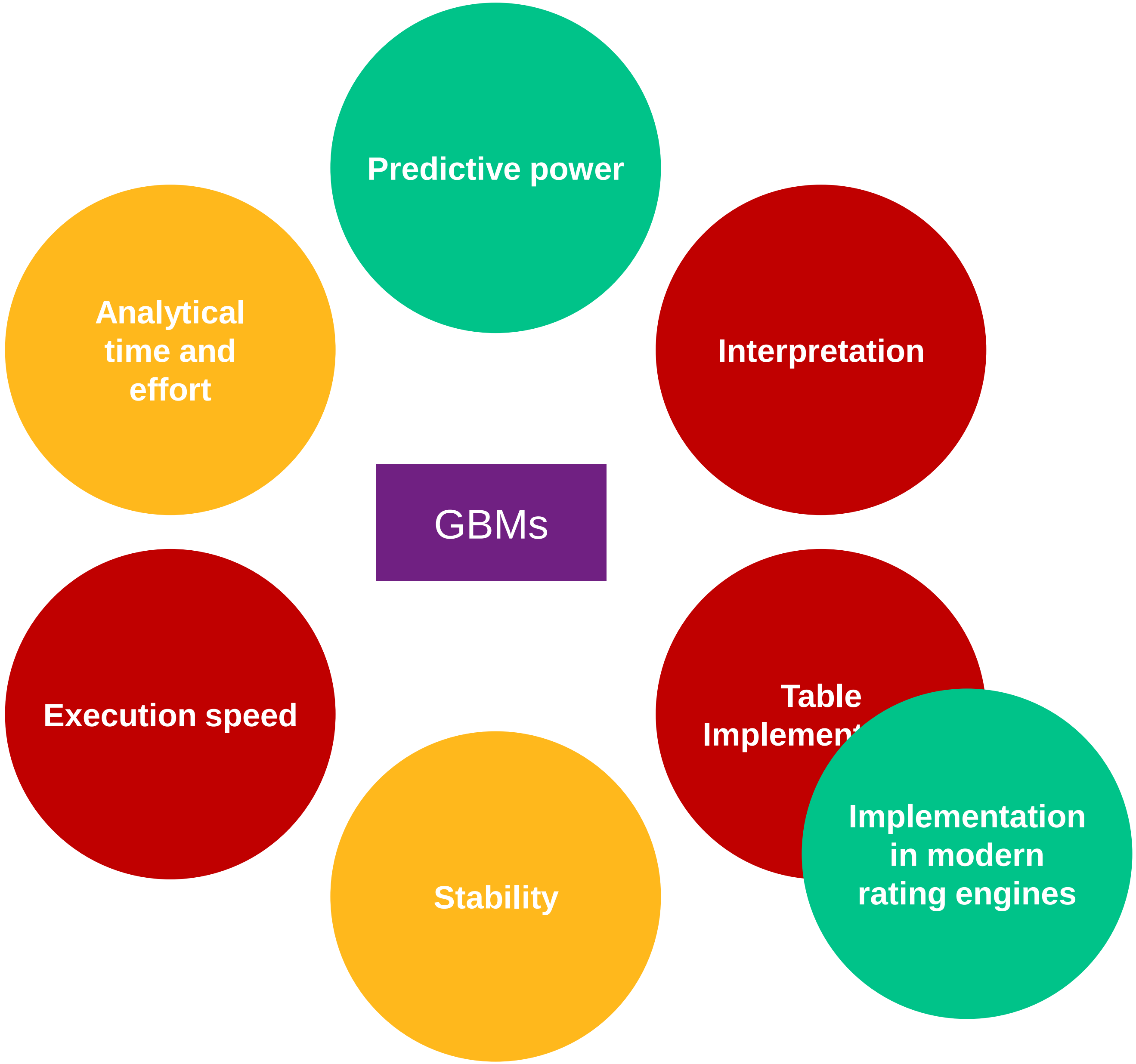
“Comfort Diagnostics”

Analytical environ-ment

Next gen rating engine

Main Policy Admin System

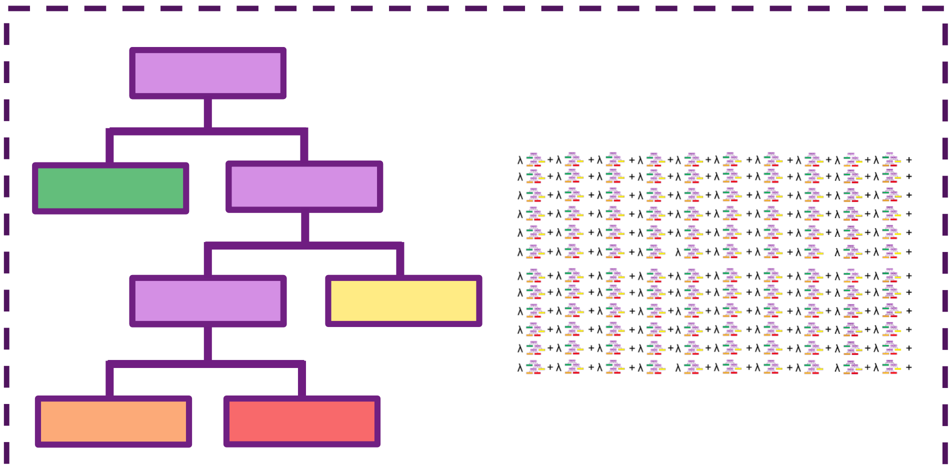
Deploy directly


Predictive power
Analytical time and effort
Interpretation
GBMs
Execution speed
Table Implemen
Implementation in modern rating engines
Stability

Practical applications of tree based methods in pricing

Streamlining factor selection

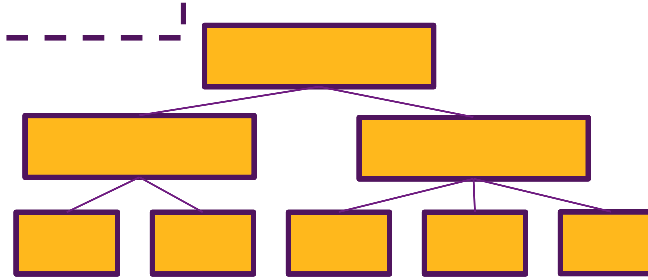
Price sharpening



Underwriting expansion

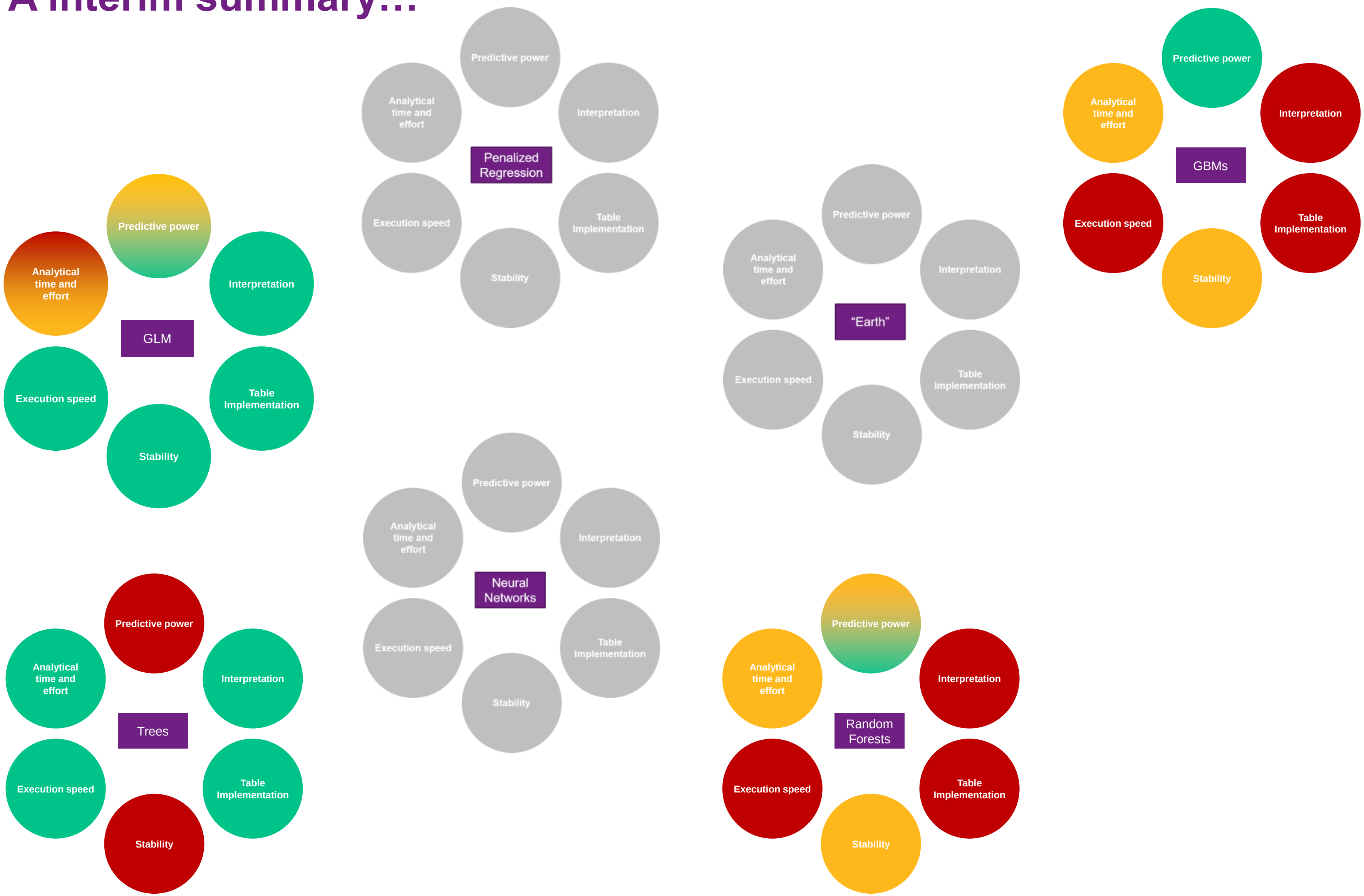
Geodemographic information

Large claims pricing



Modelling hierarchies

A interim summary…



Machine Learning in Pricing

Conclusions (Part 1)

- There are many forms of ML models
- New data and feature/response engineering generally add more value than new methods BUT we need to continuously explore which methods work on which problems
- Traditional measures of prediction value may not reflect applications in insurance
- And it’s not all about predictive power anyway – other criteria are important

- GBMs can provide predictive lift benefits by capturing higher order effects … BUT
  - Can you cope with not seeing the model and instead use broad diagnostics
  - Effort is required to expose/understand higher order effects in an expeditious manner
  - How will business leaders and regulators respond to this method?
  - Do you have the software and hardware to fit to large dataset
  - Do you have a rating engine that can implement a GBM

- More methods, insights and conclusions to follow in Part 2…

What's coming in Session 2?

Agenda
Context of machine learning in pricing
Session 1:
Decision trees Random forests Gradient boosting machines
Session 2:
"Earth" **Penalized regression** **Neural networks**
Conclusions
Q&A

Objective: to give you a working knowledge of some machine learning methods that may be used to improve GLM results and/or offer valuable insights in their own right in the field of P&C insurance pricing

Questions

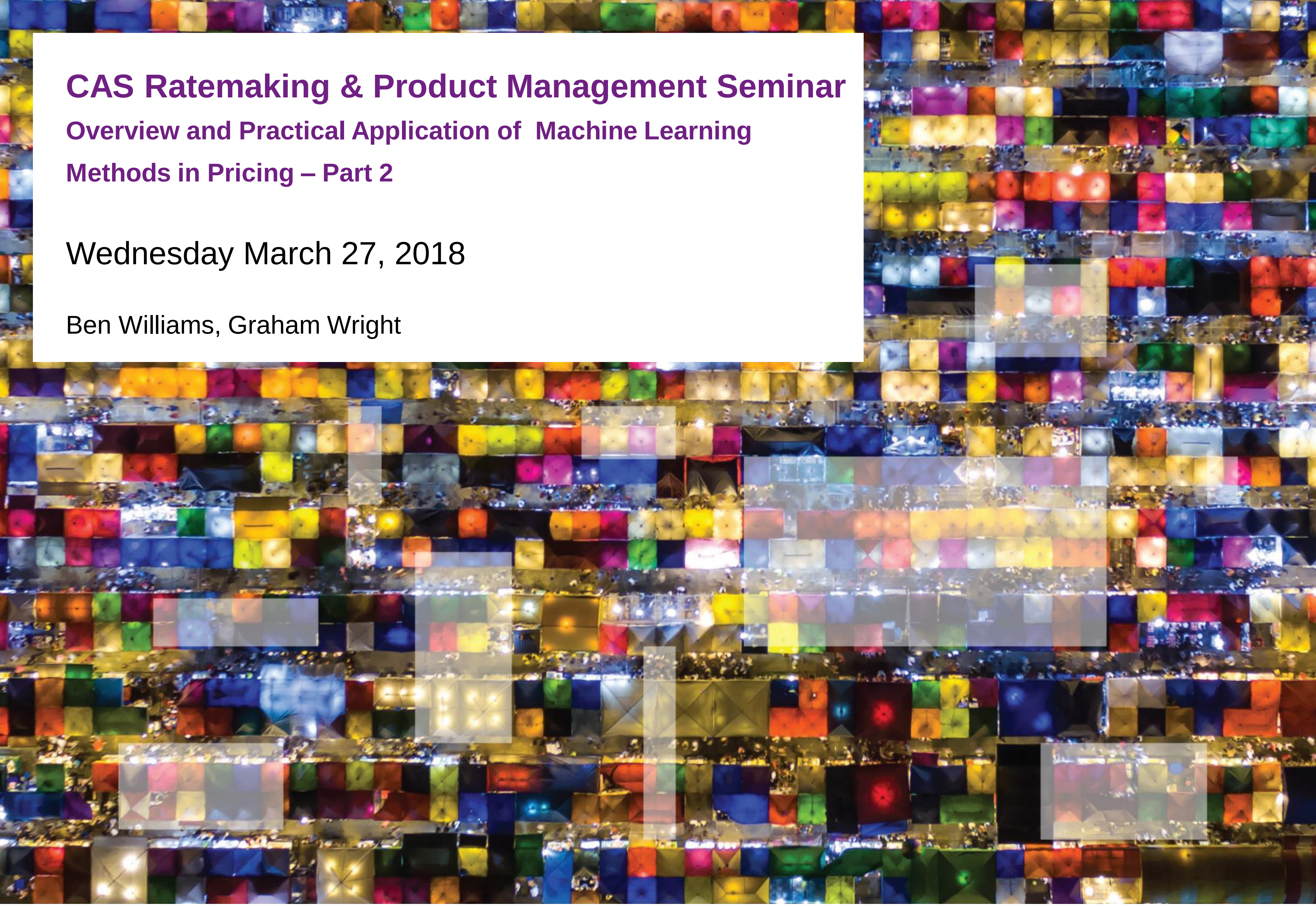
?

CAS Ratemaking & Product Management Seminar

Overview and Practical Application of Machine Learning Methods in Pricing – Part 2

Wednesday March 27, 2018

Ben Williams, Graham Wright



WillisTowersWatson

Agenda

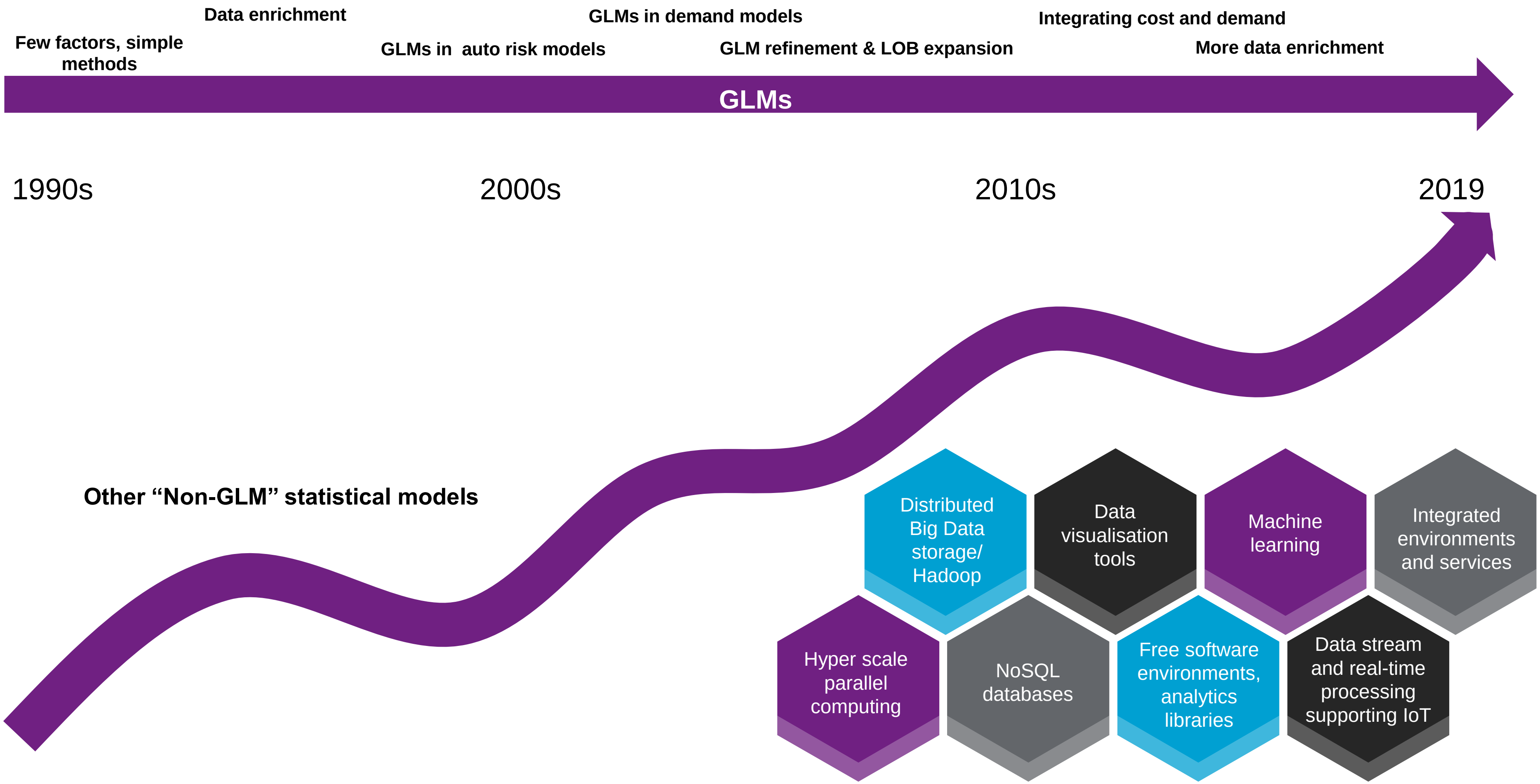
Agenda
Context of machine learning in pricing
Session 1:
Decision trees **Random forests** **Gradient boosting machines**
Session 2:
“Earth” **Penalized regression** **Neural networks**
Conclusions
Q&A

Objective: to give you a working knowledge of some machine learning methods that may be used to improve GLM results and/or offer valuable insights in their own right in the field of P&C insurance pricing

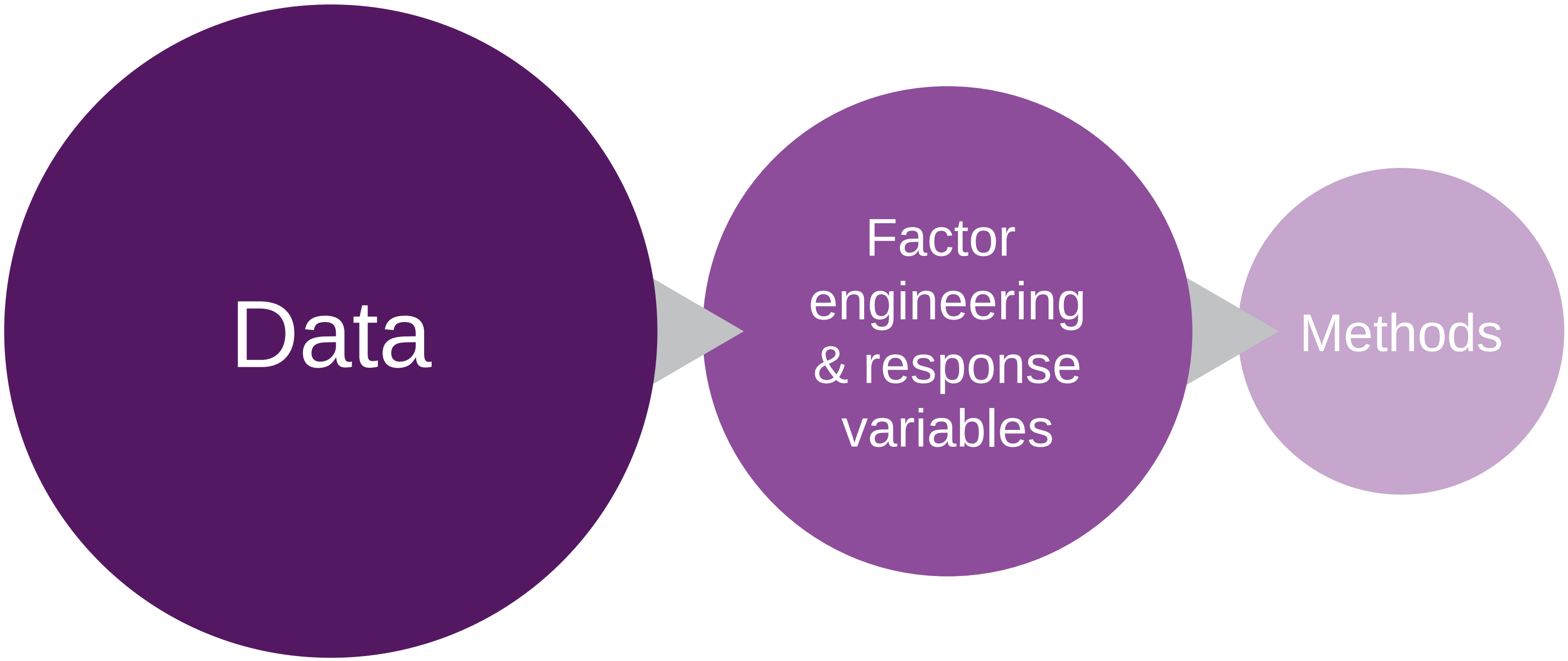
What are these machine learning methods?

Ensembles	Classifications Trees	"Earth"	Regression Trees	Gradient Boosting Machines
K-nearest Neighbors	Elastic Net	Neural Networks	Naïve Bayes	Random Forests
K-Means Clustering	Principal Components Analysis	Lasso	Support Vector Machines	Ridge Regression

This is not new….

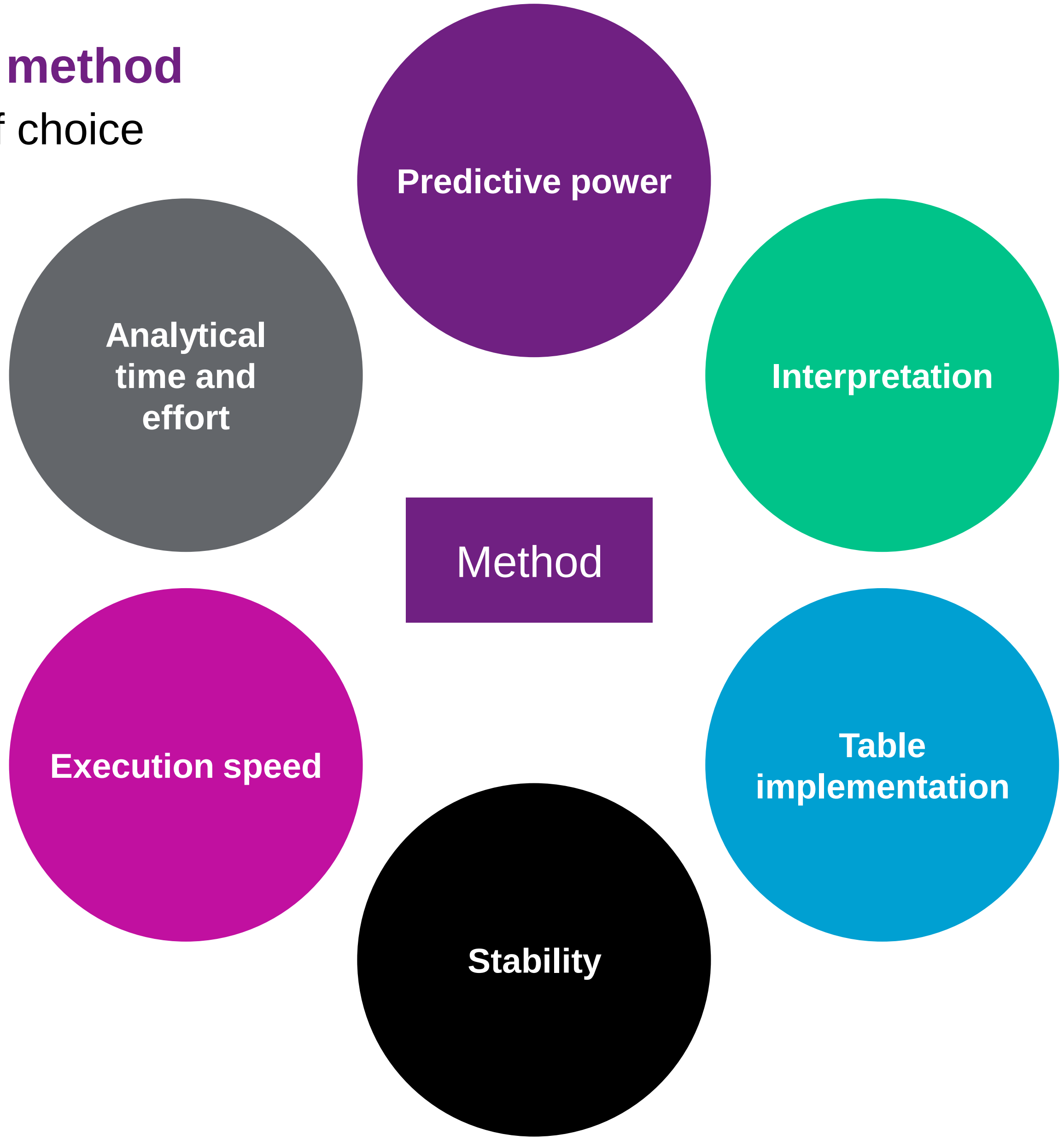


Is it really all about the method?

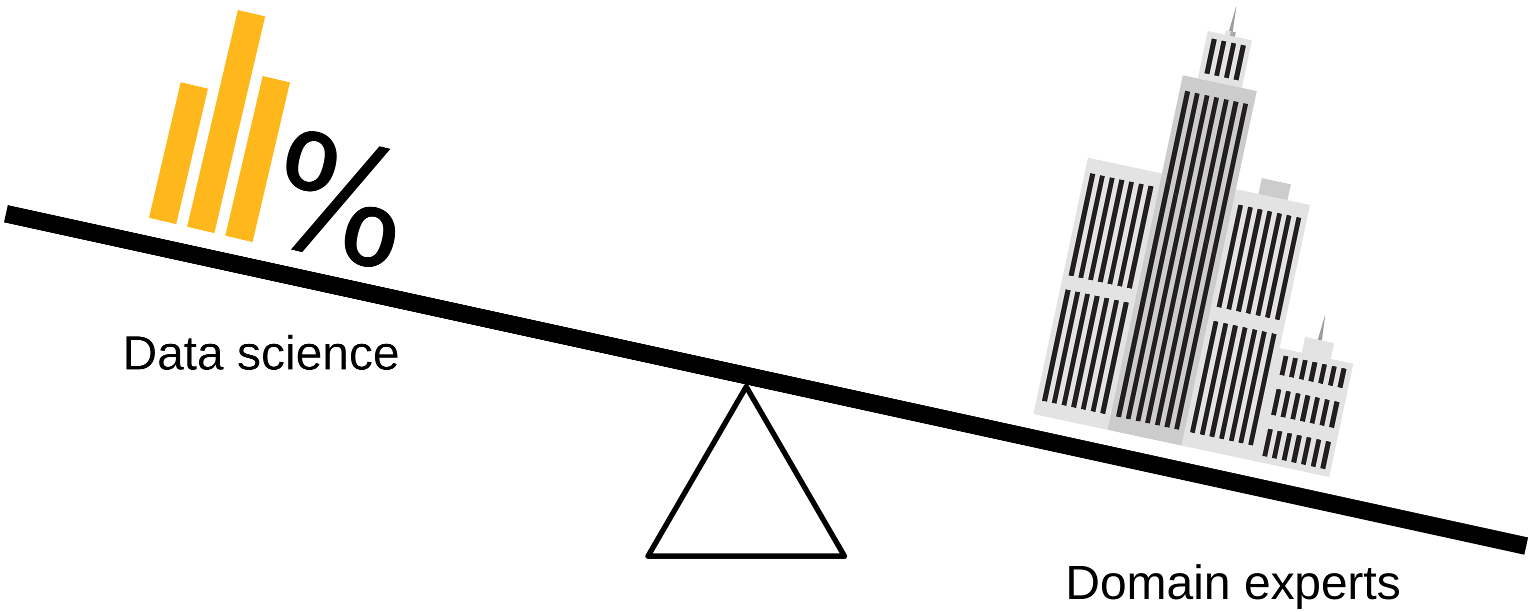


Choosing a method

Dimensions of choice



It’s domain expertise that helps decide



Financial value estimate

- Errors in insurance pricing are not symmetrical
- Financial benefit can be estimated

Example results redacted from printed version

Illustrative results

Model	Gini	Gini improvement	Gini rank	Loss ratio @ elasticity 6	Loss ratio rank	Loss ratio @ elasticity 2	Loss ratio rank
GLM (main factor removed)	0.318	-2.6%	4	-0.9%	4	-0.4%	4
GLM (minor factor removed)	0.322	-1.3%	3	-0.4%	3	-0.2%	3
GLM	0.327	0.0%	2	0.0%	2	0.0%	2
New Model	0.330	1.0%	1	2.2%	1	0.5%	1

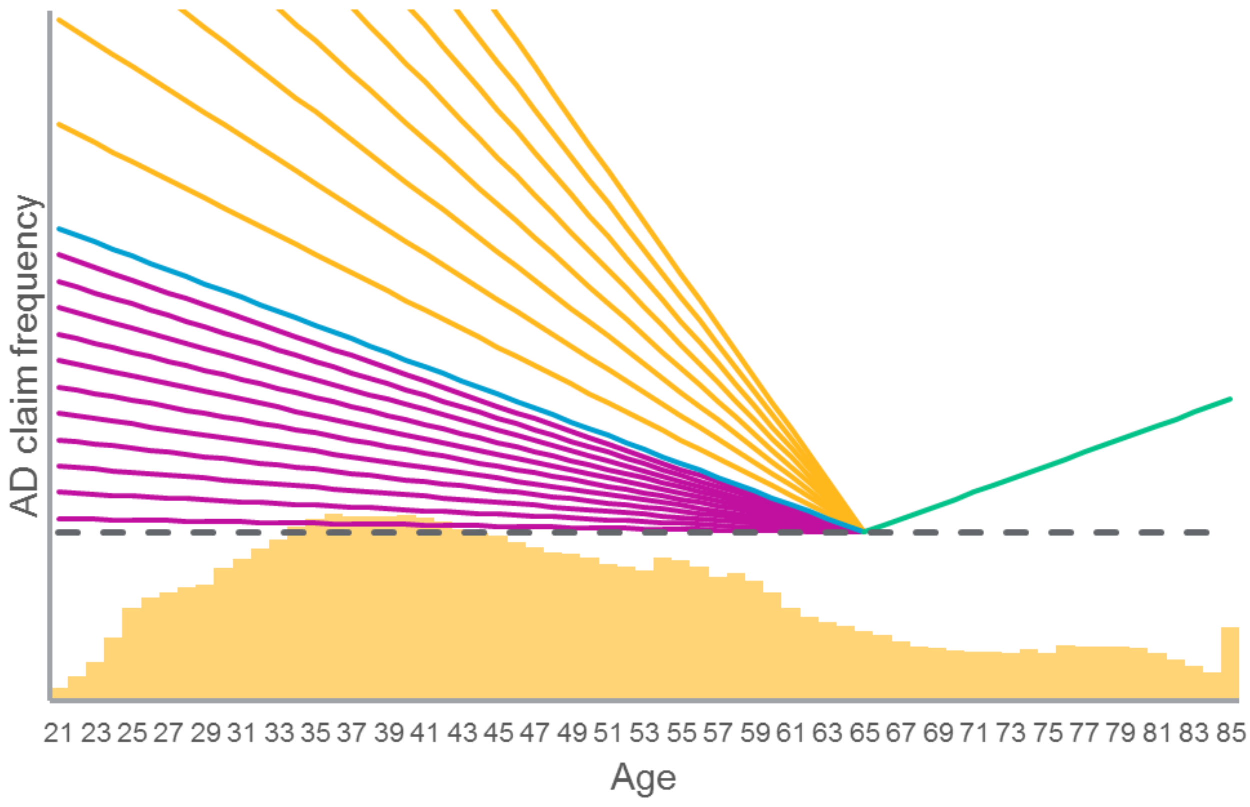
Some machine learning methods

- Ensembles
- Classifications Trees
- "Earth"
- Regression Trees
- Gradient Boosting Machines
- K-nearest Neighbors
- Elastic Net
- Neural Networks
- Naïve Bayes
- Random Forests
- K-Means Clustering
- Principal Components Analysis
- Lasso
- Support Vector Machines
- Ridge Regression

Focus on “Earth”

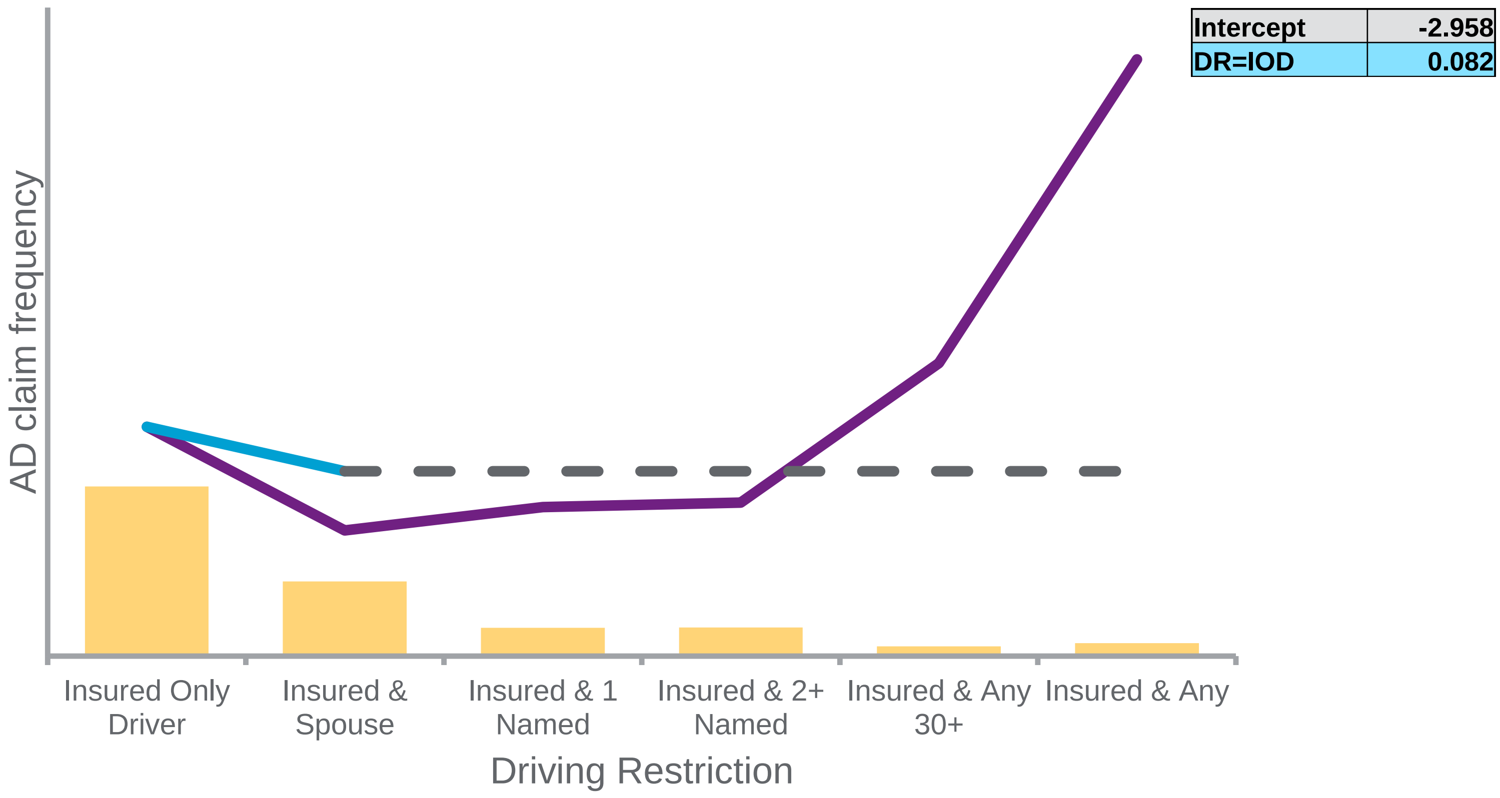
"Earth"

Multivariate adaptive regression splines ("Earth")



Multivariate adaptive regression splines ("Earth")

Categorical factors



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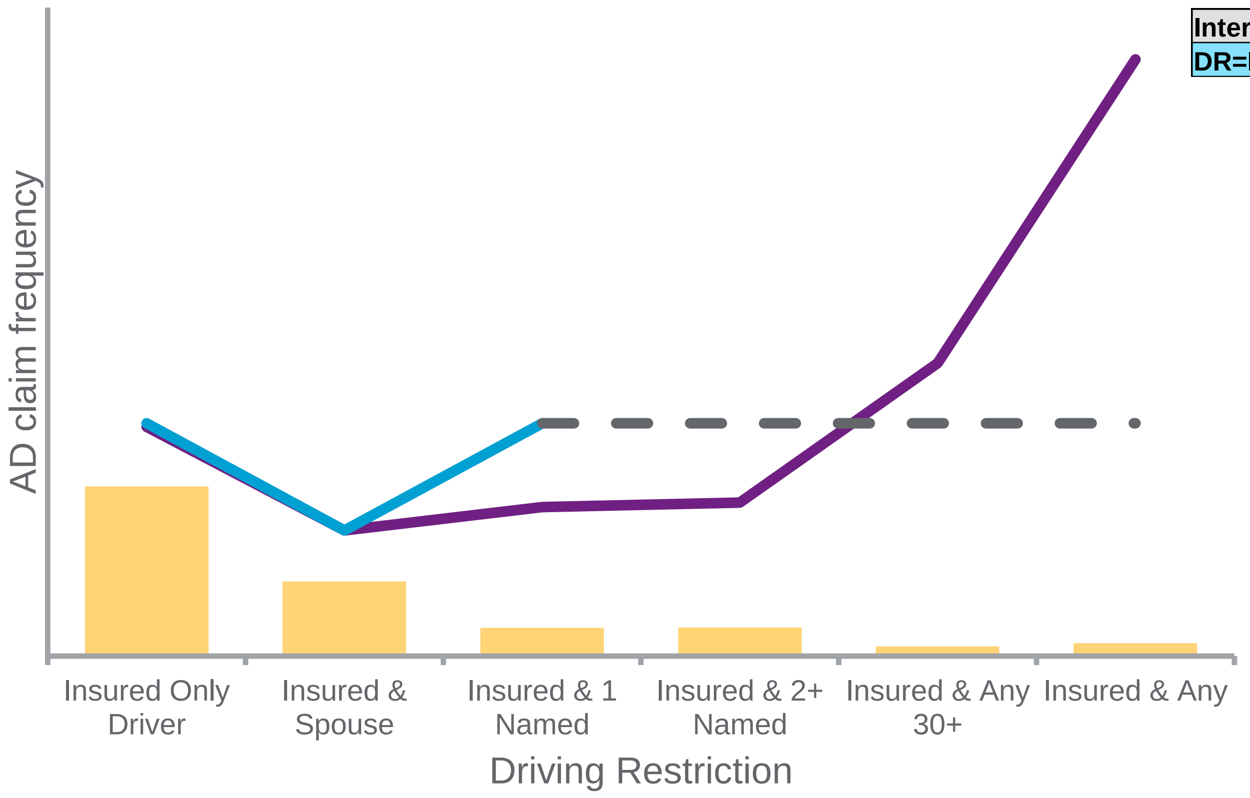
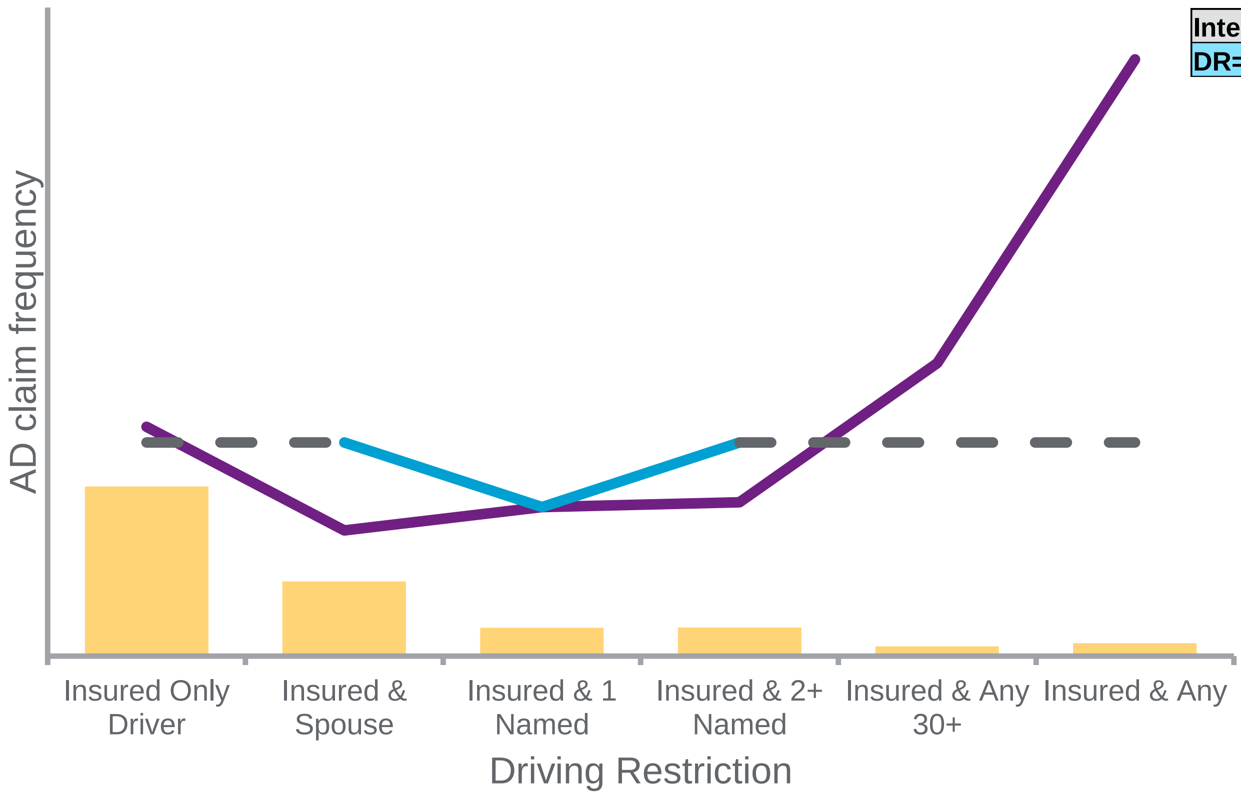


Intercept	-2.869
DR=I&S	-0.198

Multivariate adaptive regression splines (“Earth”)

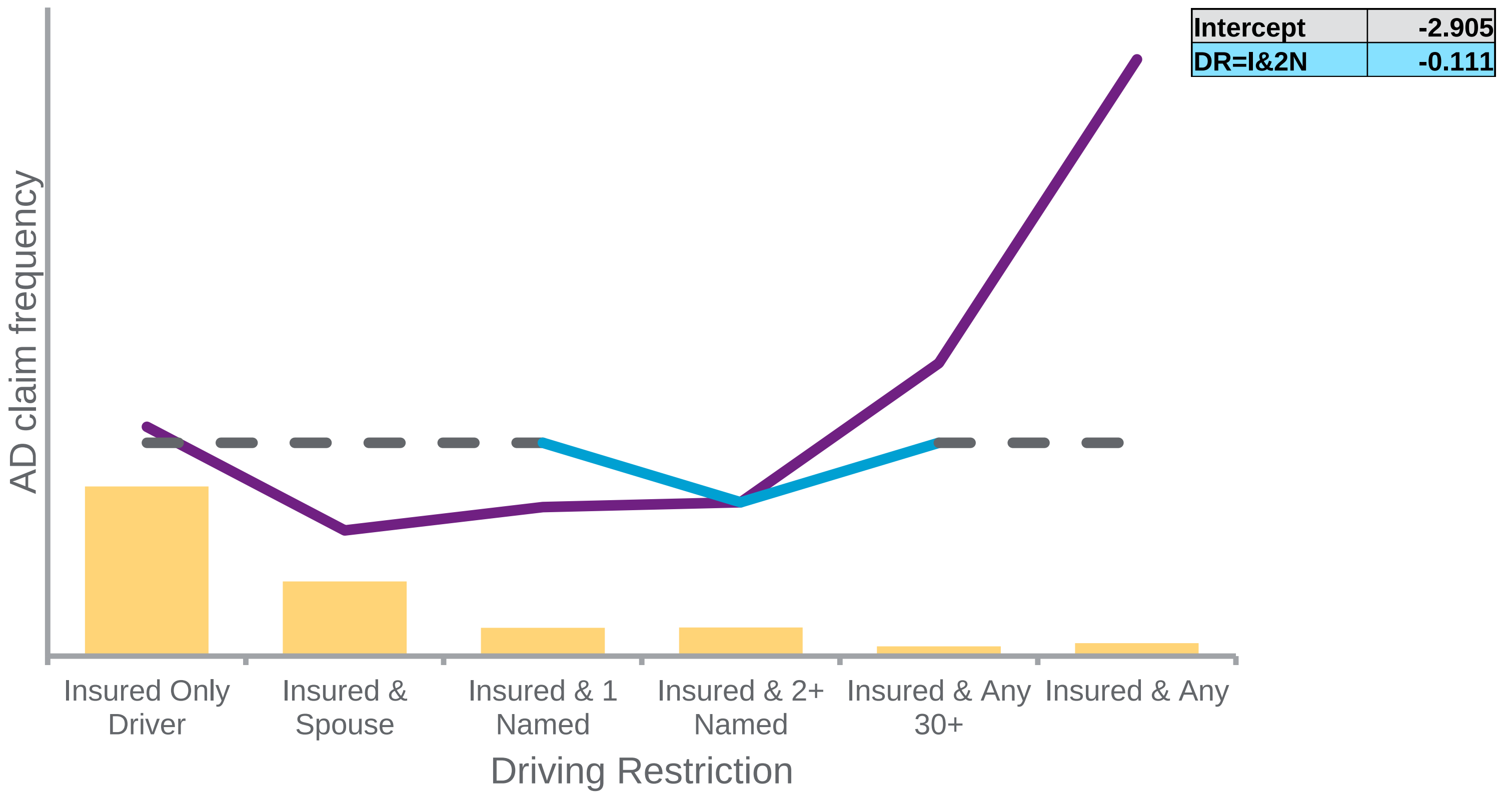
Categorical factors



Intercept	**-2.905**
DR=I&1N	**-0.120**

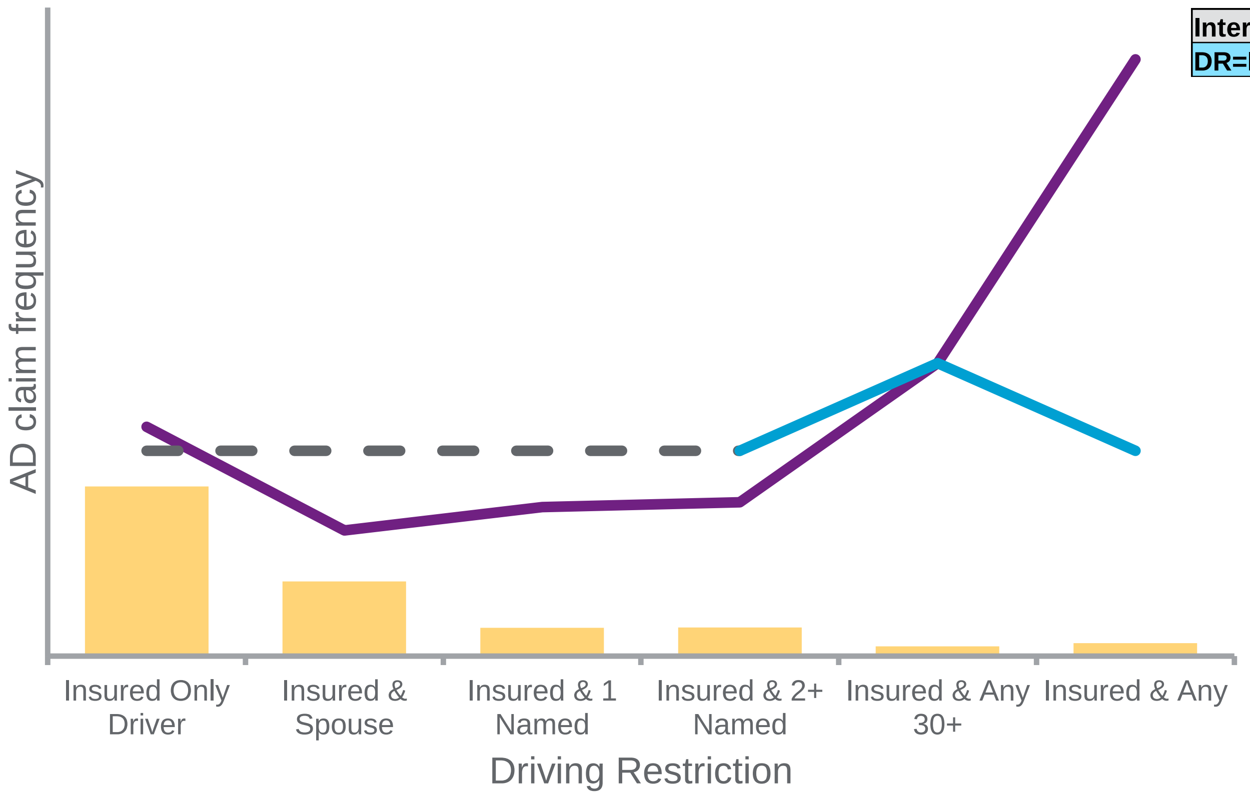
Multivariate adaptive regression splines ("Earth")

Categorical factors



Multivariate adaptive regression splines ("Earth")

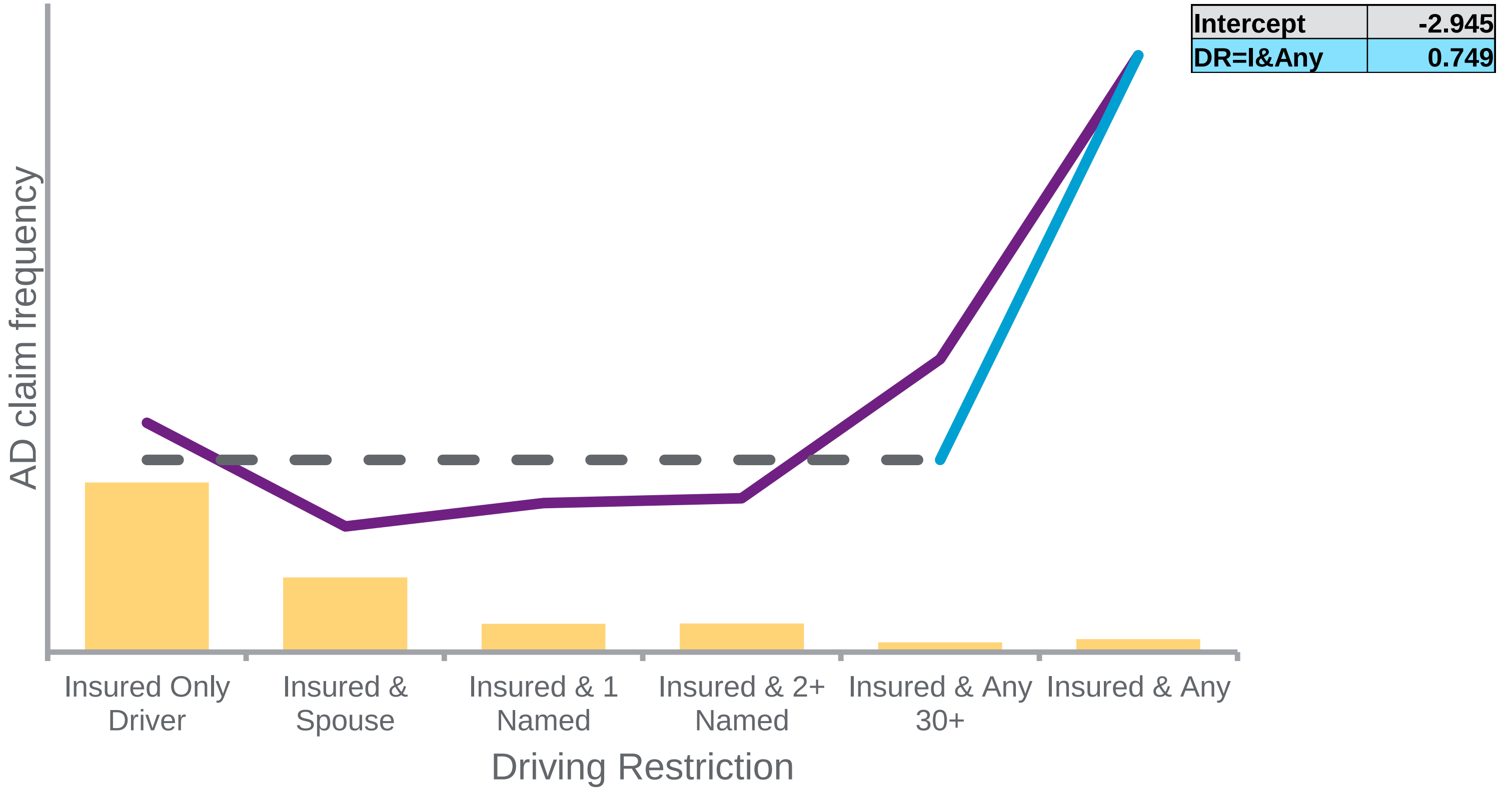
Categorical factors



Intercept	-2.920
DR=I&Any30+	0.162

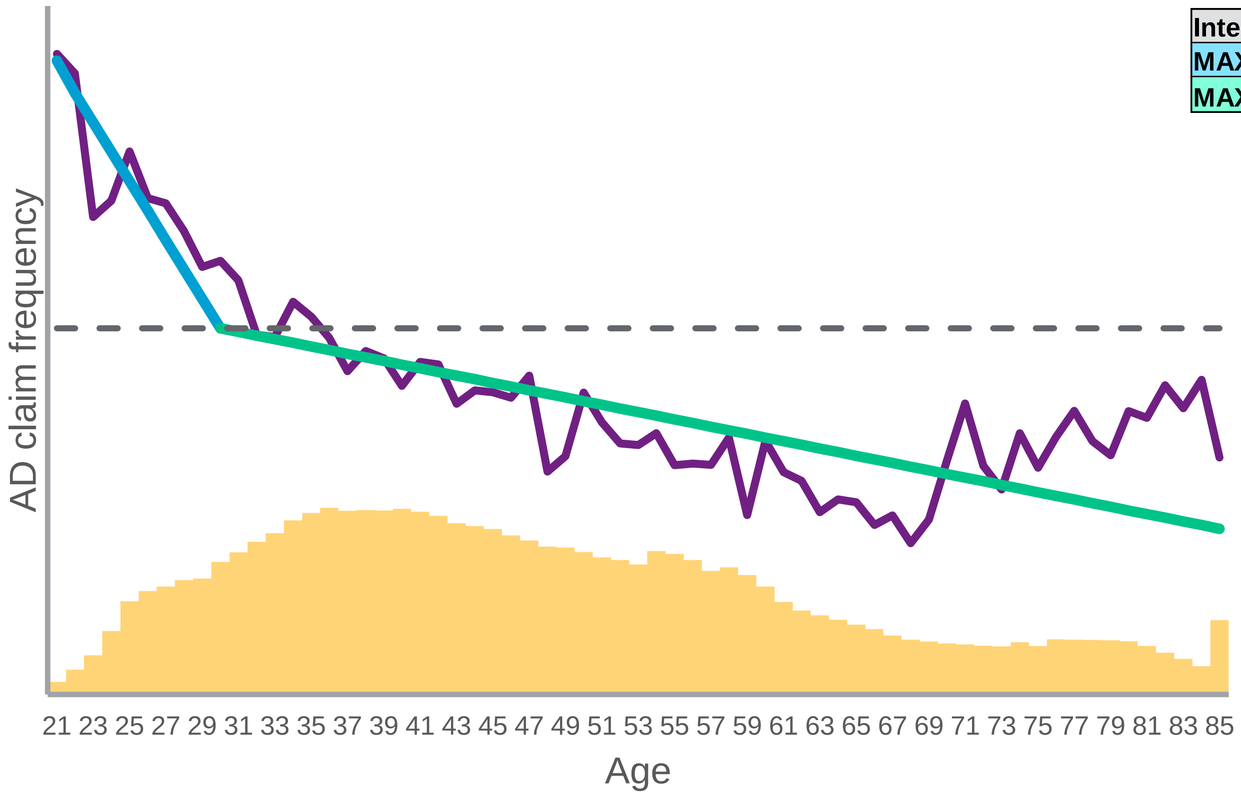
Multivariate adaptive regression splines (“Earth”)

Categorical factors



Multivariate adaptive regression splines (“Earth”)

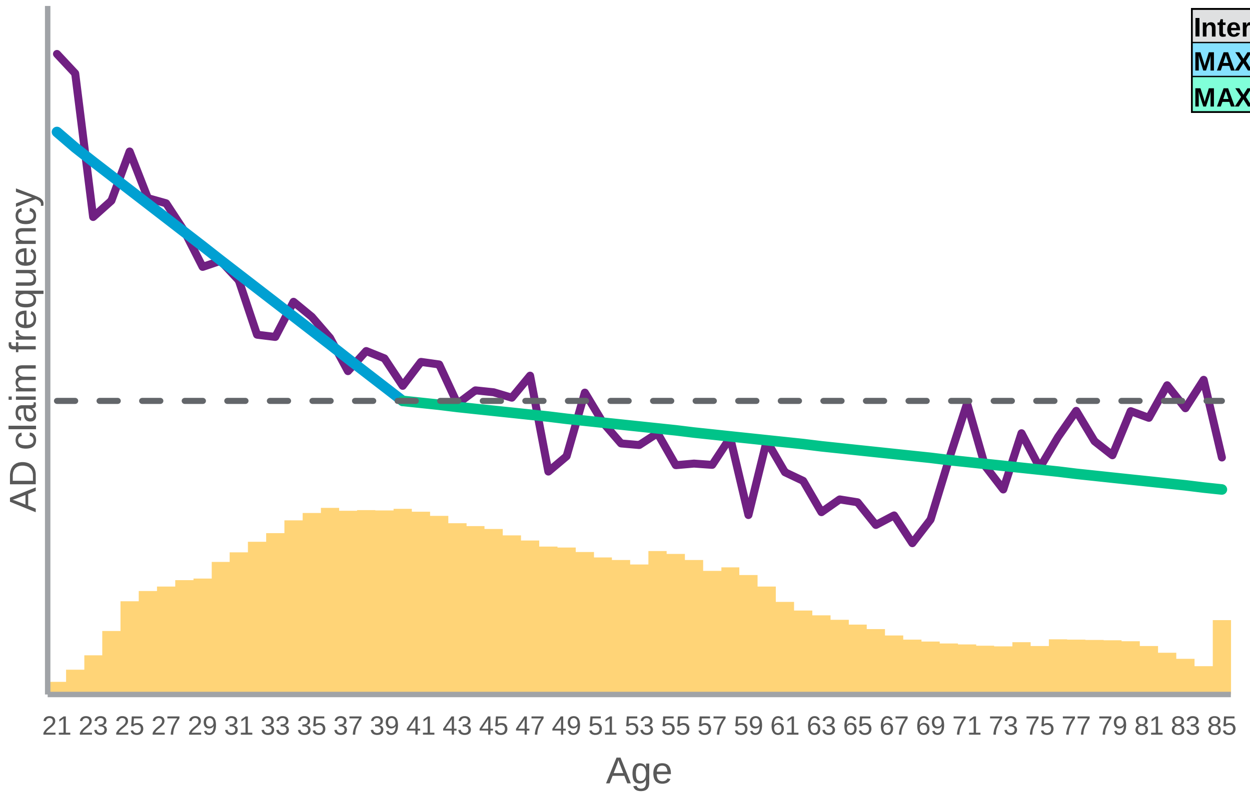
Numerical factors



Intercept	**-2.815**
MAX(30-Age,0)	**0.051**
MAX(Age-30,0)	**-0.006**

Multivariate adaptive regression splines ("Earth")

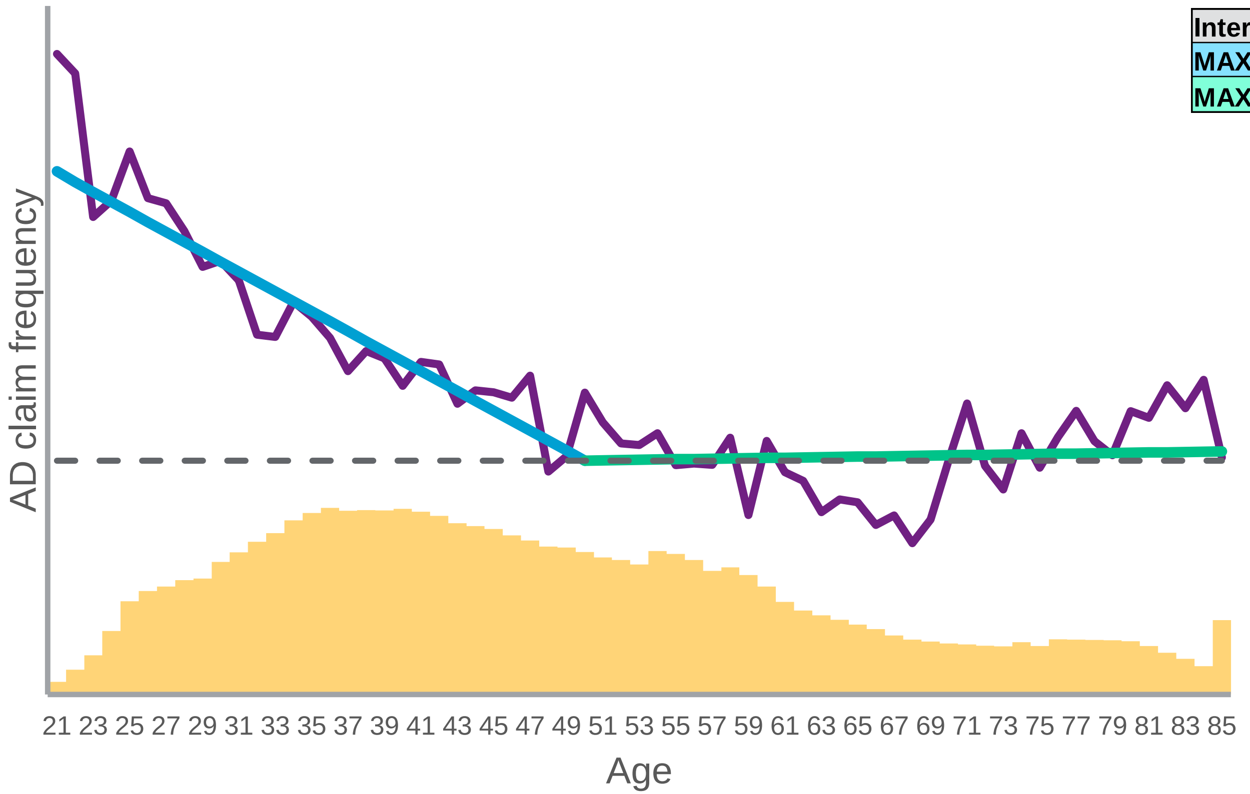
Numerical factors



Intercept	-2.931
MAX(40-Age,0)	0.025
MAX(Age-40,0)	-0.003

Multivariate adaptive regression splines (“Earth”)

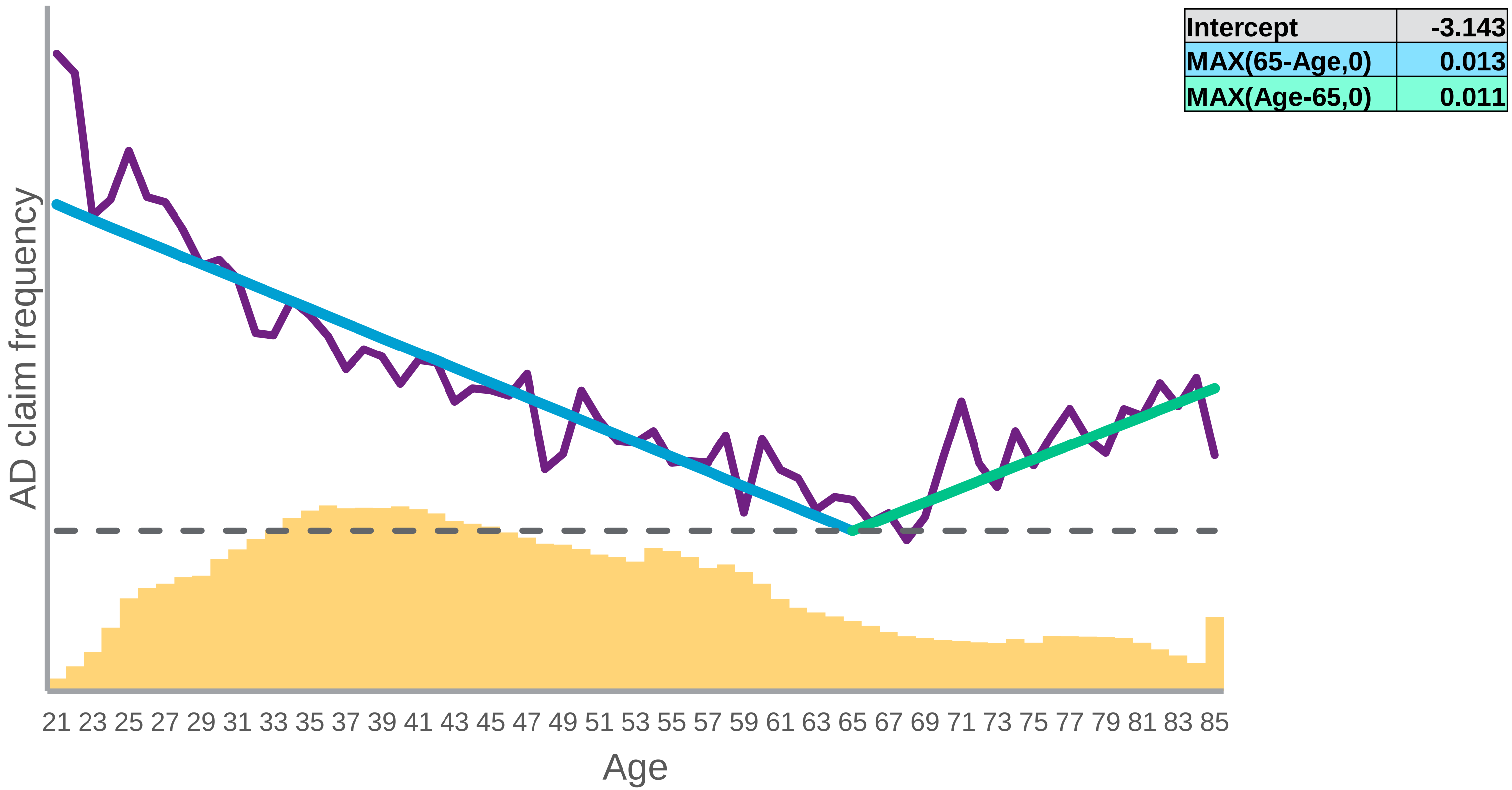
Numerical factors



Intercept	**-3.026**
MAX(50-Age,0)	**0.017**
MAX(Age-50,0)	**0.000**

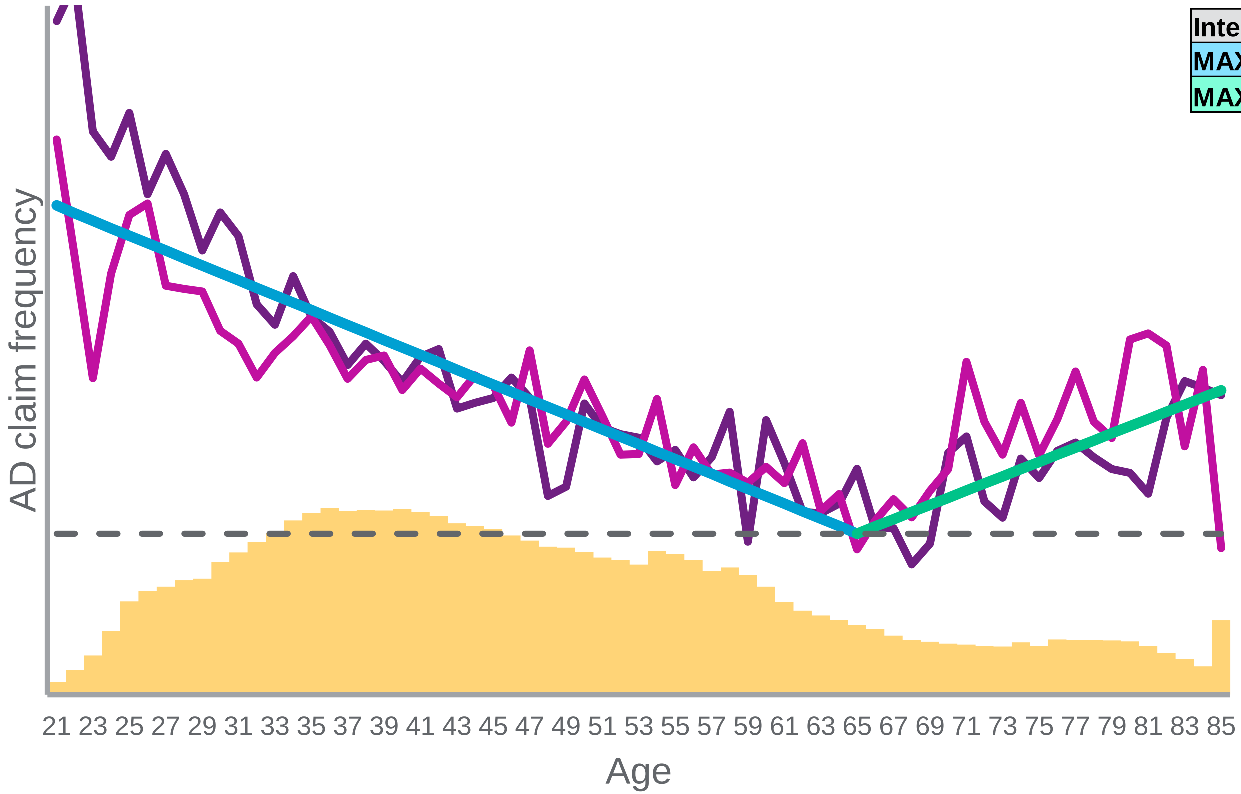
Multivariate adaptive regression splines ("Earth")

Numerical factors



Multivariate adaptive regression splines ("Earth")

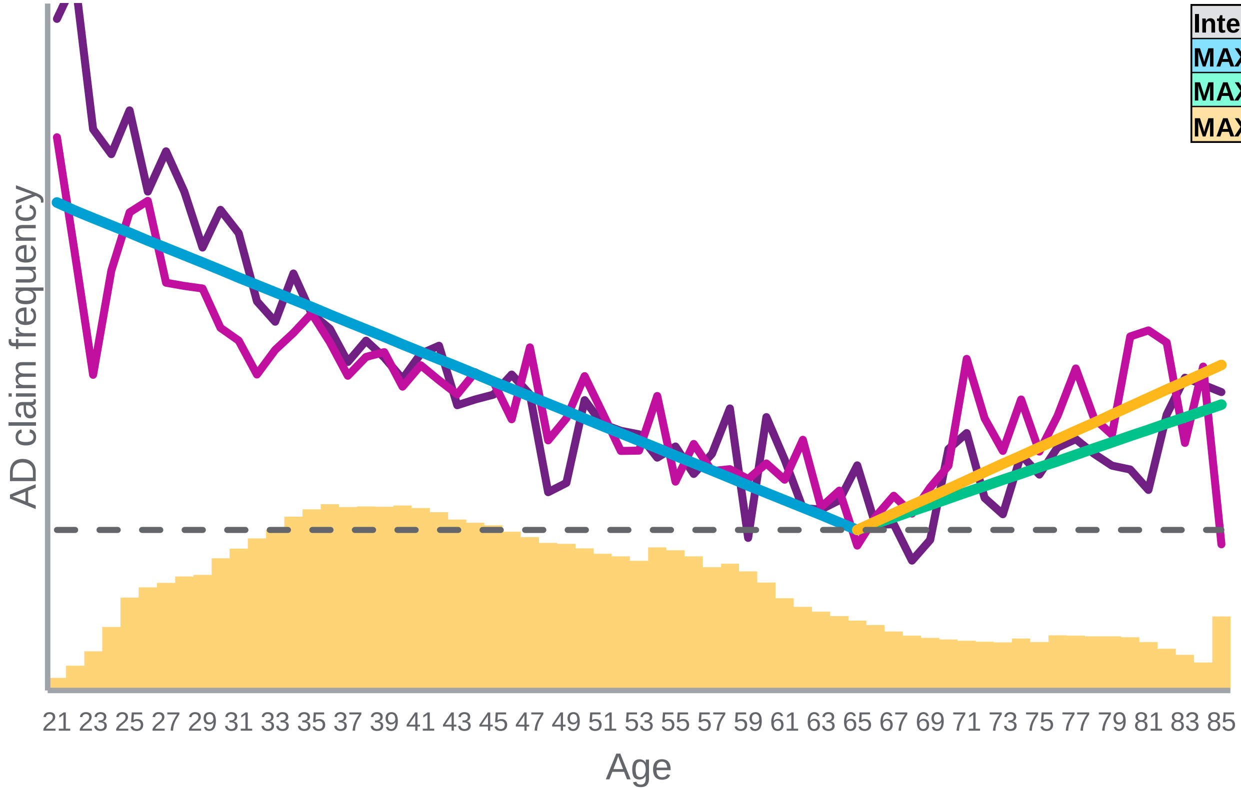
Interactions



Intercept	-3.143
MAX(65-Age,0)	0.013
MAX(Age-65,0)	0.011

Multivariate adaptive regression splines ("Earth")

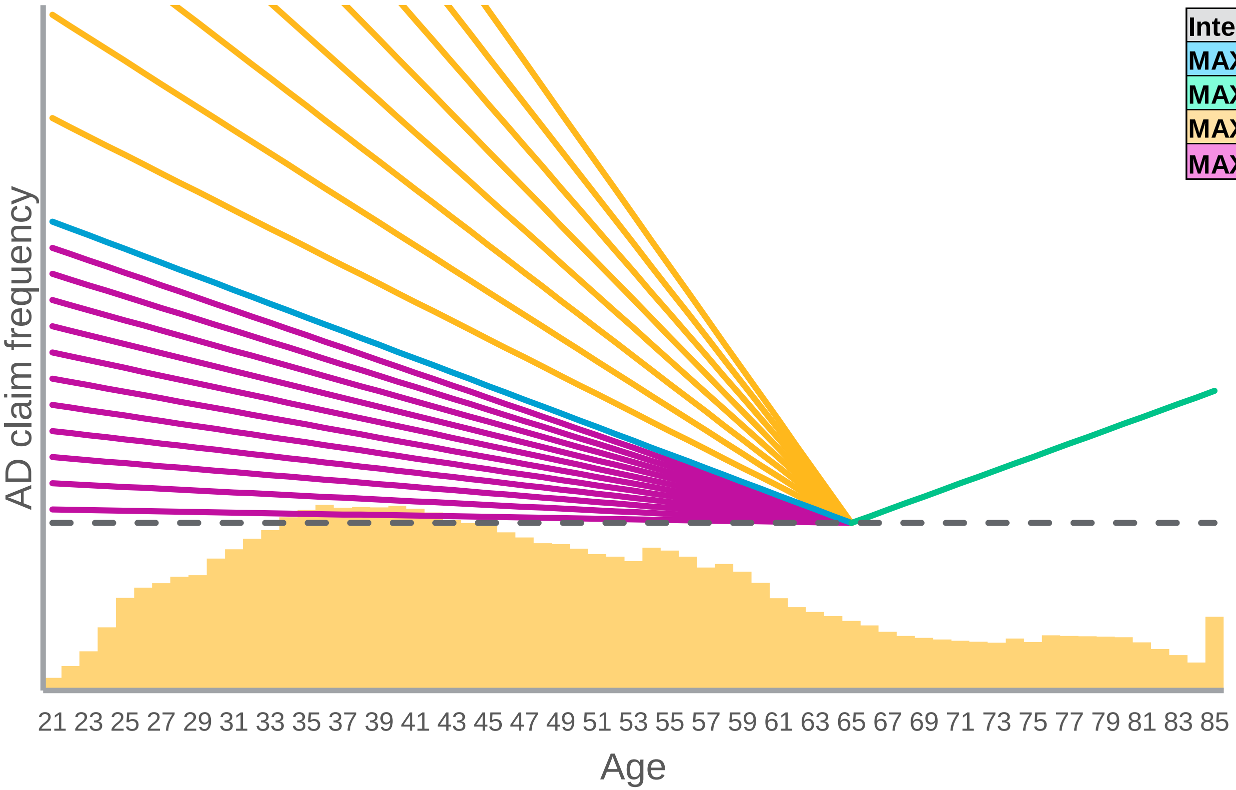
Interactions



Intercept	-3.143
MAX(65-Age,0)	0.013
MAX(Age-65,0)	0.010
MAX(Age-65,0)*(Gender=F)	0.003

Multivariate adaptive regression splines (“Earth”)

Interactions



Intercept	**-3.131**
MAX(65-Age,0)	**0.011**
MAX(Age-65,0)	**0.011**
MAX(65-Age,0)*MAX(VG-12,0)	**0.004**
MAX(65-Age,0)*MAX(12-VG,0)	**-0.001**

Multivariate adaptive regression splines (“Earth”)

Advantages

- Minimum manual setup required
- Fast run time
- Highly interpretable results

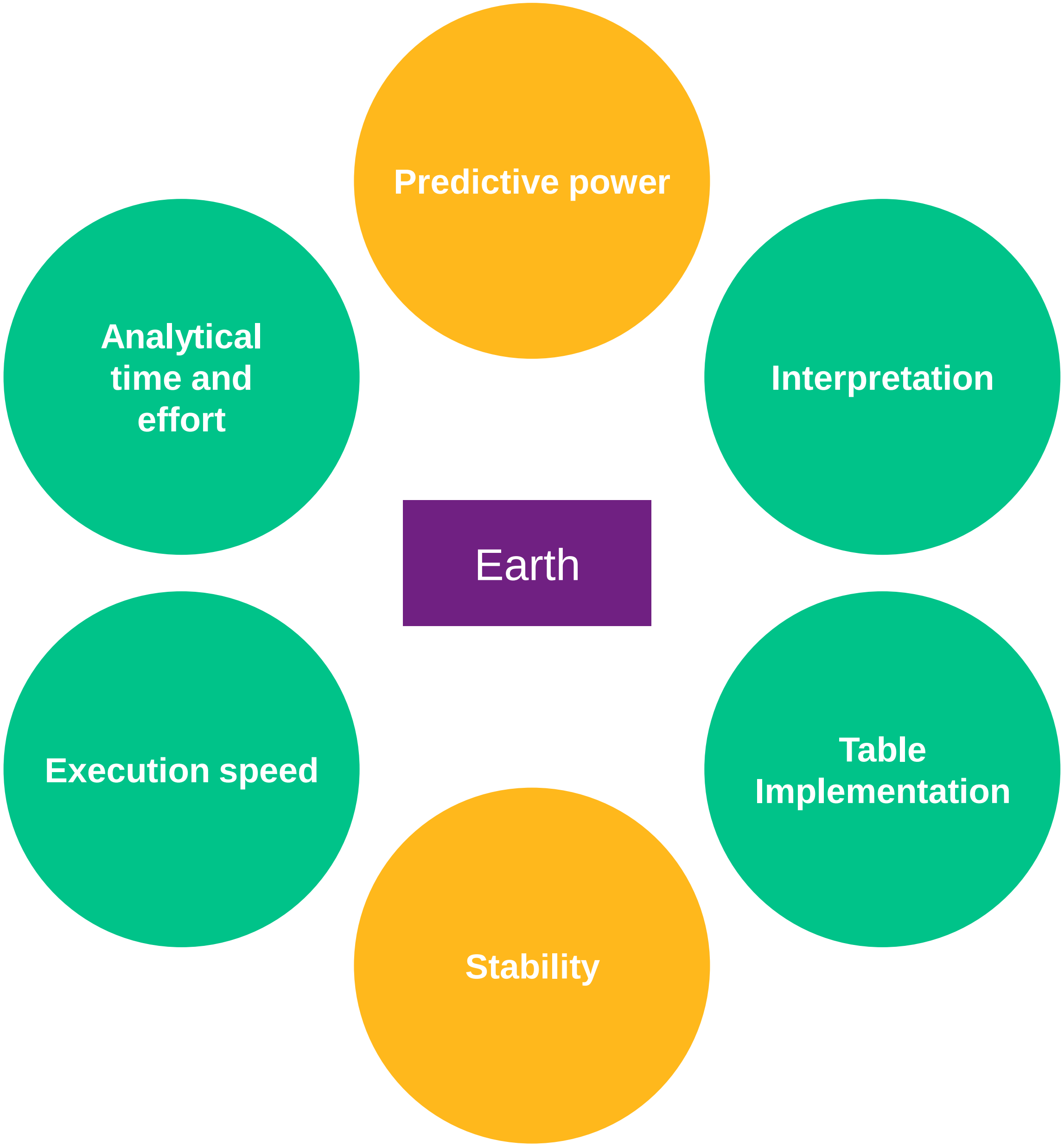
Disadvantages

- Model will contain discontinuities around knot points
- Hand-crafting likely to improve results

Intercept	0.412
UsuallyPayANNUAL	0.543
h(Log_Premium – 6.314)	0.432
h(Age-35)	-0.329
UsuallyPayANNUAL * h(Log_Premium-6.5673)	0.00654
Homeowner	-0.0291
etc	….

How might “Earth” be applied?

- Historically pricing models have been fit by coverage and/or peril – are these still the most suitable splits?
- When should models be split/combined? (e.g., homeowners and landlords policies or fire and lightning perils)
- How many models should we build and what should they predict?
- Increasing use of machine learning to answer these structural/strategic questions


Predictive power
Analytical time and effort
Interpretation
Earth
Execution speed
Table Implementation
Stability

Some machine learning methods

- Ensembles
- Classifications Trees
- "Earth"
- Regression Trees
- Gradient Boosting Machines
- K-nearest Neighbors
- Elastic Net
- Neural Networks
- Naïve Bayes
- Random Forests
- K-Means Clustering
- Principal Components Analysis
- Lasso
- Support Vector Machines
- Ridge Regression

Focus on Penalized Regression

Elastic Net

Lasso

Ridge Regression

Penalized Regression

Overview

GLMs

- Predictions are given by $f(\underline{x}) = g^{-1}(\mathbf{X}.\underline{\beta})$
- $\underline{\beta}$ is estimated by minimizing a loss function $L(\underline{\beta}|\mathbf{X},\underline{y})$ ($\mathbf{X}$ is data & model, $\underline{y}$ the response)

Penalized regression

- The same, except the objective function becomes $L(\underline{\beta}|\mathbf{X},\underline{y}) + \lambda.$ "Penalty on $\underline{\beta}$"

Elastic Net

$$\textbf{Minimize: } L(\beta|X,y) + \boxed{\lambda_1 \sum_i |\beta_i|} + \boxed{\lambda_2 \sum_i \beta_i^2}$$

Lasso **-** just the **blue** part

- Penalty reduces insignificant parameter values to zero – useful for variable selection

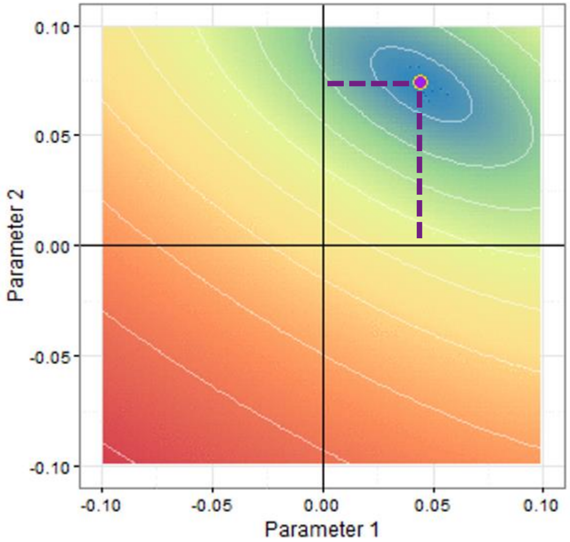
Ridge **-** just the **purple** part regression models

- Penalty heavily penalize extreme parameters, but do not reduce parameters to zero

Penalized Regression

GLM

f($\underline{x}$) = g^{-1}($\mathbf{X}.\underline{\beta}$) where $\underline{\beta}$ estimated by minimizing $L(\beta|X,y)$



Penalized Regression

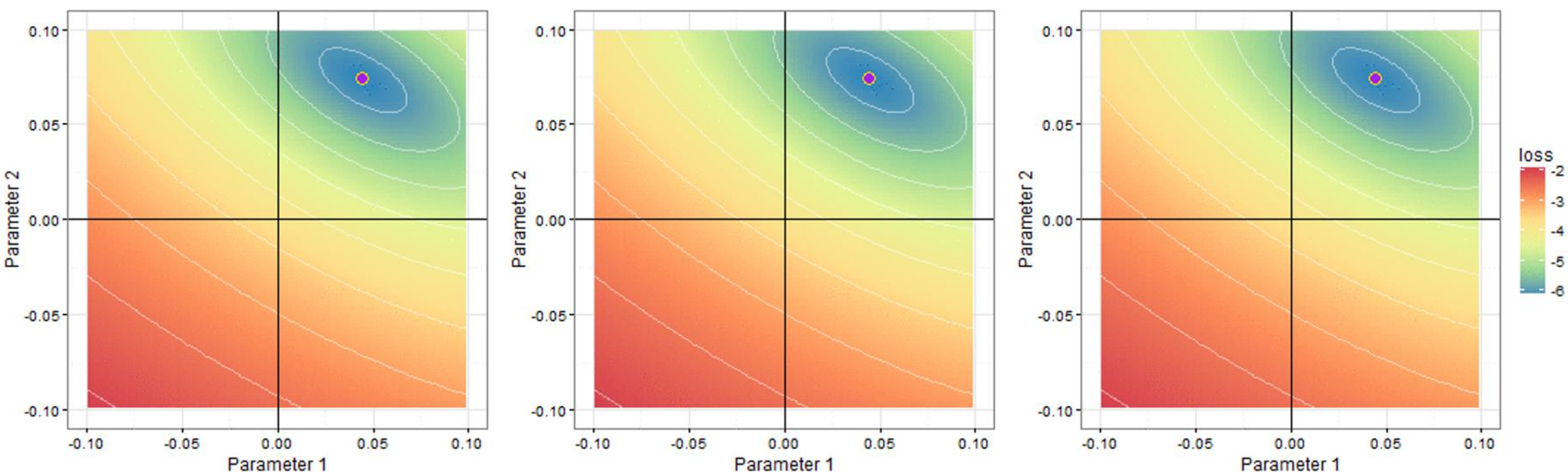
f(x) = $g^{-1}(\mathbf{X}.\beta)$ where β estimated by minimizing

GLM Lasso Ridge

$$L(\beta|X,y) + \lambda_1 \sum_i |\beta_i| + \lambda_2 \sum_i \beta_i^2$$

Elastic Net

Ridge $\sum_i \beta_i^2$ **Elastic Net** **Lasso** $\sum_i |\beta_i|$



Heavily penalize large parameters, but does not reduce parameters to zero

Mix of the two

Penalty reduces insignificant parameter values to zero - useful for variable selection

Penalized Regression

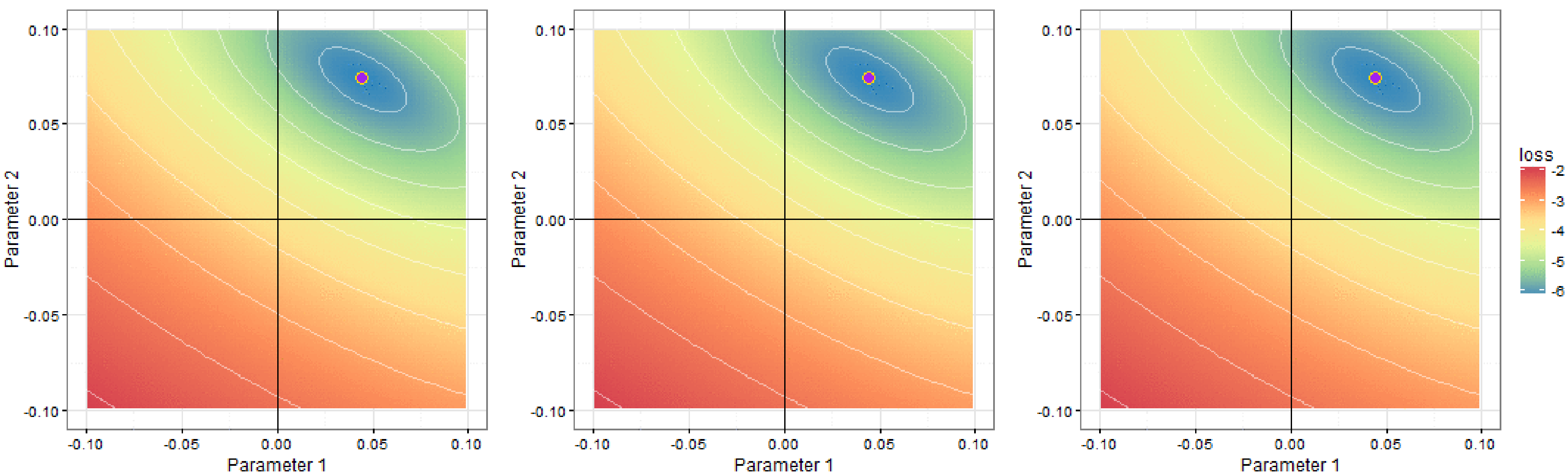
f(x) = $g^{-1}(\mathbf{X}.\beta)$ where β estimated by minimizing

GLM **Lasso** **Ridge**

$$L(\beta|X,y) + \boxed{\boxed{\lambda_1 \sum_i |\beta_i|} + \boxed{\lambda_2 \sum_i \beta_i^2}}$$

Elastic Net

Ridge $\sum_i \beta_i^2$ **Elastic Net** **Lasso** $\sum_i |\beta_i|$



Heavily penalize large parameters, but does not reduce parameters to zero

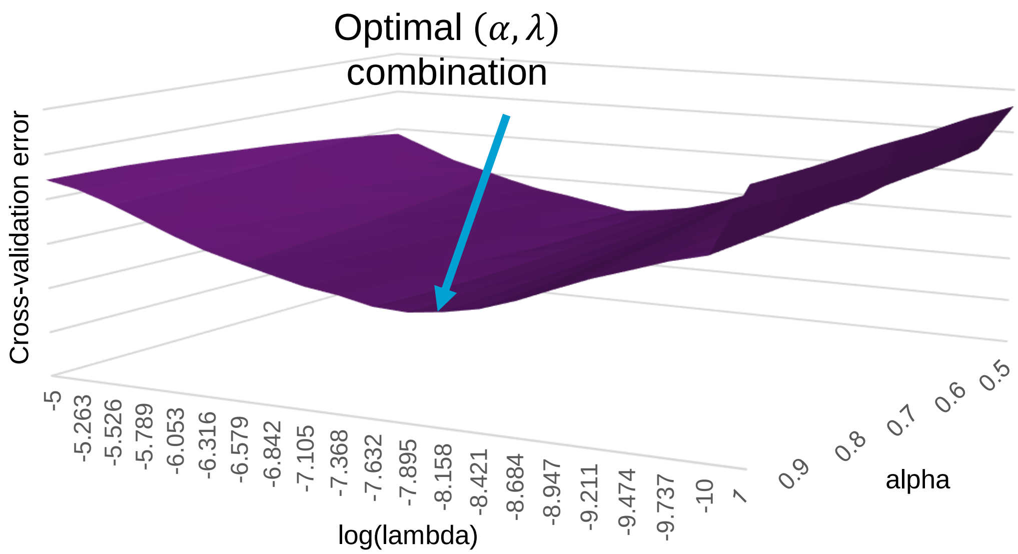
Mix of the two

Penalty reduces insignificant parameter values to zero - useful for variable selection

Penalized Regression

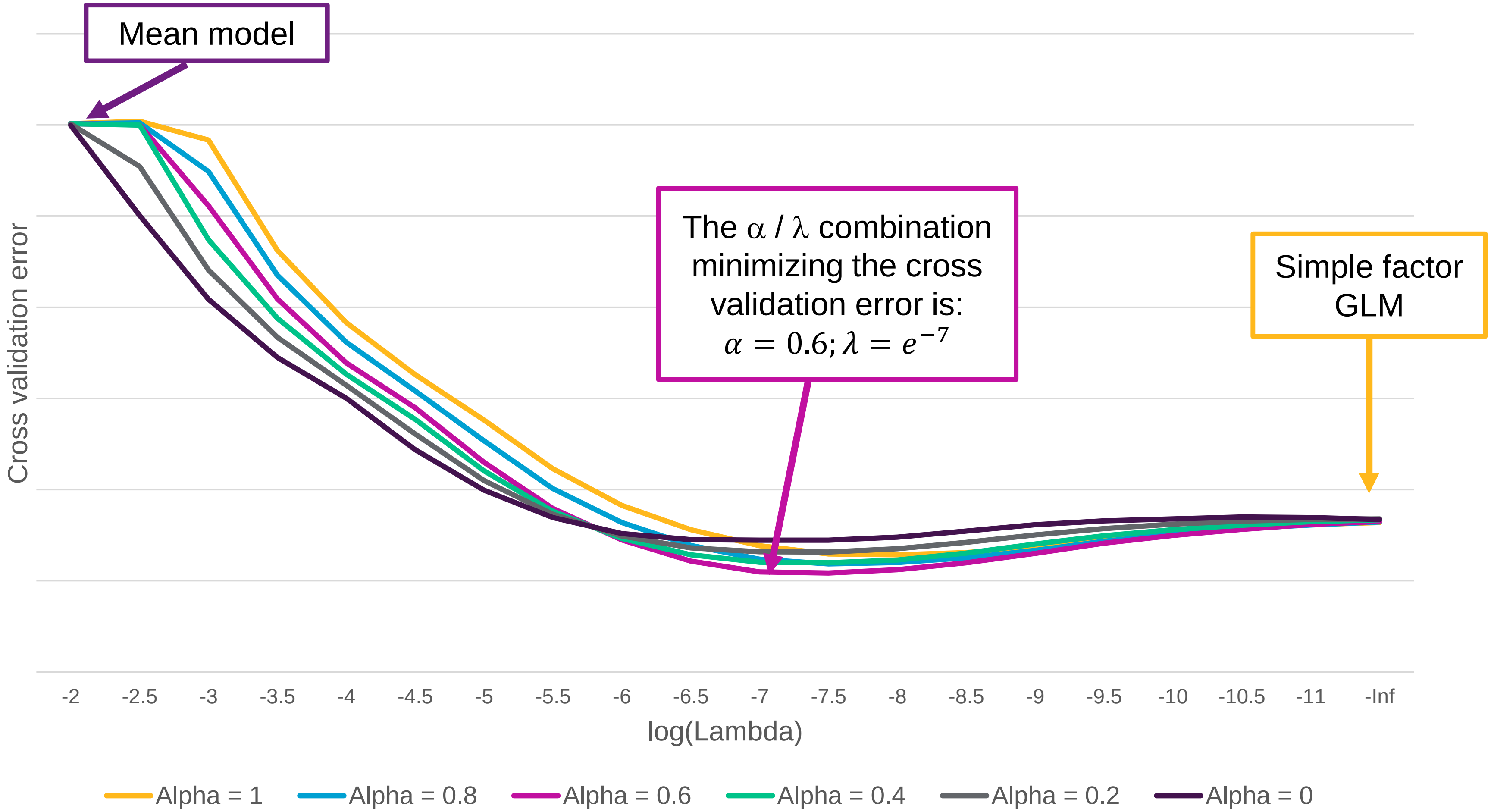
Parameter selection

- Minimize: $L(\beta|X, y) + \lambda_1 \sum_i |\beta_i| + \lambda_2 \sum_i \beta_i^2$
- Penalty parameters can be re-written: $\lambda_1 = \lambda\alpha, \quad \lambda_2 = \lambda\left(\frac{1-\alpha}{2}\right)$
- α controls the mixture between Lasso ($\alpha = 1$) and Ridge ($\alpha = 0$)
- λ controls the overall size of the penalty
- λ, α selected using cross-validation
- Factors automatically selected from initial set!



Penalized Regression

Parameter selection - example

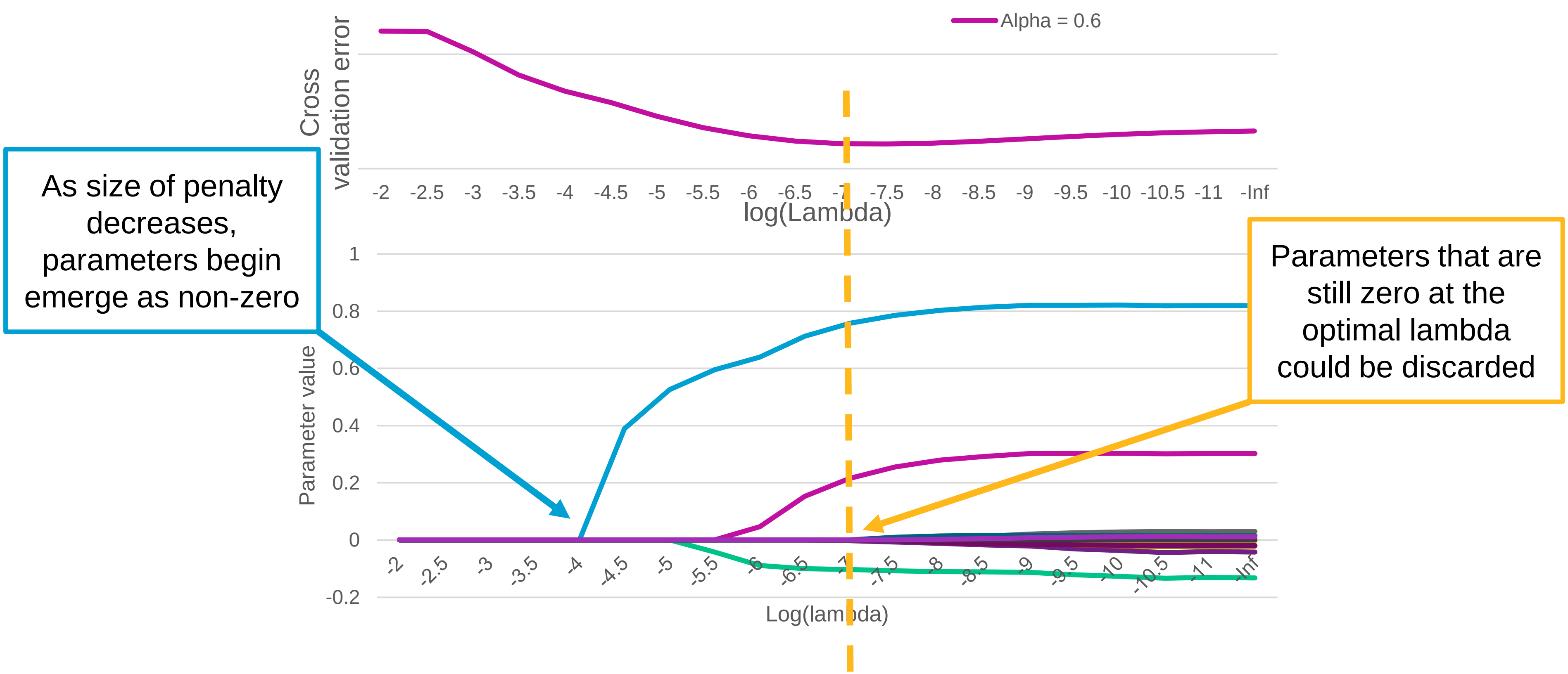


Models range from Lasso (α =1) to Ridge (α =0)

Penalized Regression

Parameter selection - example

- The fitting process can be investigated to help with feature selection



Penalized Regression

Parameter selection

There are costs to allowing too many factors in our models

- Computational cost of processing more data / fitting more parameters
- Time cost of analysts needing to consider more potential effects
- Reduced comprehensibility of interplay of many different correlated effects in our models
- Financial cost of licensing and maintaining many different data sources, and hosting/updating tables to use them in rating
- Performance cost as increased number of tests makes it more likely that we will find false-positives and overfit to noise in our data

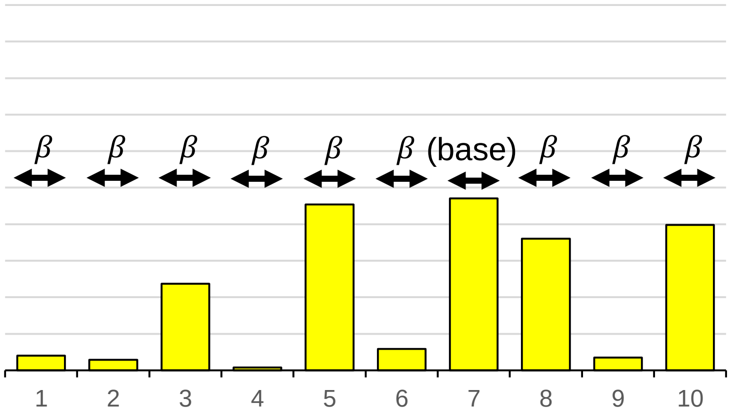
Penalized Regression

Vehicle classification – categorical factors

Exposure	# Claims	Policy Factors	Ext Code	Vehicle Make	…	Engine Size
1	0	…	0000001	Ford	…	1400
1	1	…	0000002	Porsche	…	3000
0.5	0	…	0000001	Ford	…	1400
1	0	…	0000001	Ford	…	1400
0.5	1	…	0000003	Honda	…	1300
1	0	…	0000002	Porsche	…	3000
1	0	…	0000001	Ford	…	1400
0.5	0	…	0000003	Honda	…	1300
0.3	0	…	0000003	Honda	…	1300
1	1	…	0000002	Porsche	…	3000
1	0	…	0000001	Ford	…	1400
…	…	…	….	…	…	…

Make = Ford	Make = Honda	…	Make = Porsche
1	0	…	0
0	0	…	1
1	0	…	0
1	0	…	0
0	1	…	0
0	0	…	1
1	0	…	0
0	1	…	0
0	1	…	0
0	0	…	1
1	0	…	0
…	…	…	…

- One 0-1 column per level (excluding base)
- Equivalent to adding a "simple factor" to a GLM



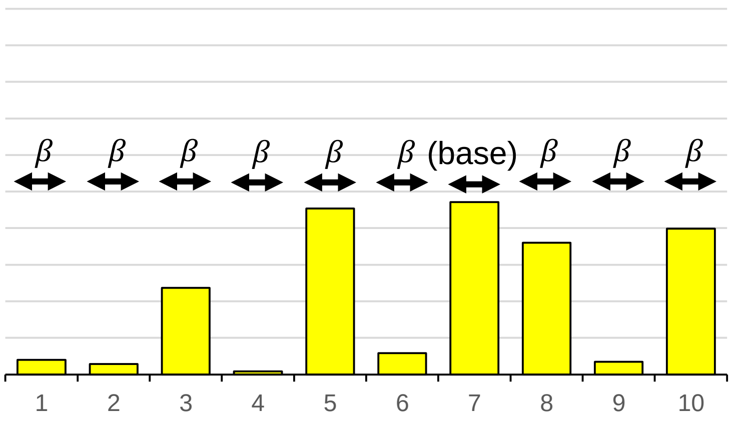
Penalized Regression

Vehicle classification – numerical factors

Exposure	# Claims	Policy Factors	Ext Code	Vehicle Make	..	Engine Size
1	0	…	0000001	Ford	..	1400
1	1	…	0000002	Porsche	..	3000
0.5	0	…	0000001	Ford	..	1400
1	0	…	0000001	Ford	..	1400
0.5	1	…	0000003	Honda	..	1300
1	0	…	0000002	Porsche	..	3000
1	0	…	0000001	Ford	..	1400
0.5	0	…	0000003	Honda	..	1300
0.3	0	…	0000003	Honda	..	1300
1	1	…	0000002	Porsche	..	3000
1	0	…	0000001	Ford	..	1400
…	…	…	….	…	..	…

Engine Size = 1300	…	Engine Size = 3000
0	…	0
0	…	1
0	…	0
0	…	0
1	…	0
0	…	1
0	…	0
1	…	0
1	…	0
0	…	1
0	…	0
…	…	…

- Adding one 0-1 column per value/band allows full flexibility, but loses knowledge of ordering



Penalized Regression

Vehicle classification – numerical factors

Exposure	# Claims	Policy Factors	Ext Code	Vehicle Make	..	Engine Size
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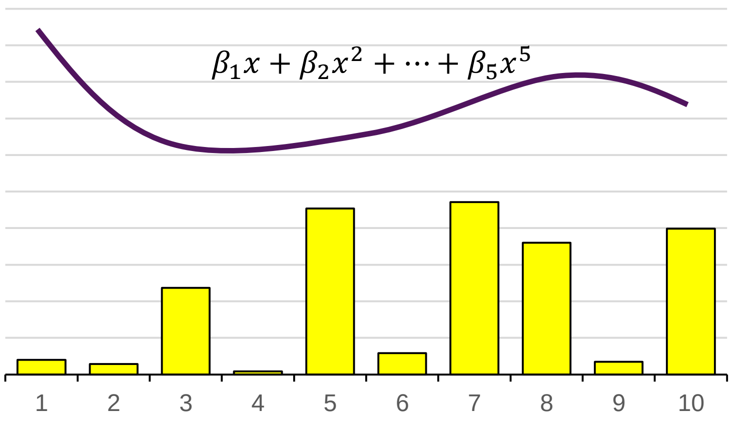
0.5	0	…	0000001	Ford	..	1400
1	0	…	0000001	Ford	..	1400
0.5	1	…	0000003	Honda	..	1300
1	0	…	0000002	Porsche	..	3000
1	0	…	0000001	Ford	..	1400
0.5	0	…	0000003	Honda	..	1300
0.3	0	…	0000003	Honda	..	1300
1	1	…	0000002	Porsche	..	3000
1	0	…	0000001	Ford	..	1400
…	…	…	….	…	..	…

Engine Size	(Engine Size)^2	…	(Engine Size)^5
1400	1960000	…	5.38E+15
3000	9000000	…	2.43E+17
1400	1960000	…	5.38E+15
1400	1960000	…	5.38E+15
1300	1690000	…	3.71E+15
3000	9000000	…	2.43E+17
1400	1960000	…	5.38E+15
1300	1690000	…	3.71E+15
1300	1690000	…	3.71E+15
3000	9000000	…	2.43E+17
1400	1960000	…	5.38E+15
…	…	…	…

- Adding one 0-1 column per value/band allows full flexibility, but loses knowledge of ordering
- Adding variates retains ordering, but limits flexibility
  - Model fit also impacted by scale of x-values as parameters are scaled, affecting the penalty size
  - Orthogonal variates/splines can help with scaling and convergence



Penalized Regression

Vehicle classification

Exposure	# Claims	Policy Factors	Ext Code	Vehicle Make	..	Engine Size
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0.5	0	…	0000001	Ford	..	1400
1	0	…	0000001	Ford	..	1400
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1	0	…	0000002	Porsche	..	3000
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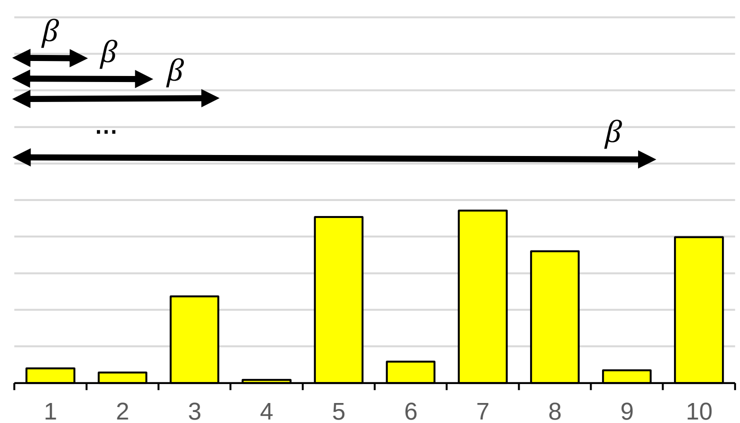
1	1	…	0000002	Porsche	..	3000
1	0	…	0000001	Ford	..	1400
…	…	…	….	…	..	…

Engine Size <= 1300	…	Engine Size <= 3000
0	…	1
0	…	1
0	…	1
0	…	1
1	…	1
0	…	1
0	…	1
1	…	1
1	…	1
0	…	1
0	…	1
…	…	…

- Adding one 0-1 column per value/band allows full flexibility, but loses knowledge of ordering
- Adding variates retains ordering, but limits flexibility
  - Model fit also impacted by scale of x-values as parameters are scaled, affecting the penalty size
  - Orthogonal variates/splines can help with scaling and convergence
- Adding a series of “less than or equal” indicators retains as much flexibility as a column per band, and also retains knowledge of ordering



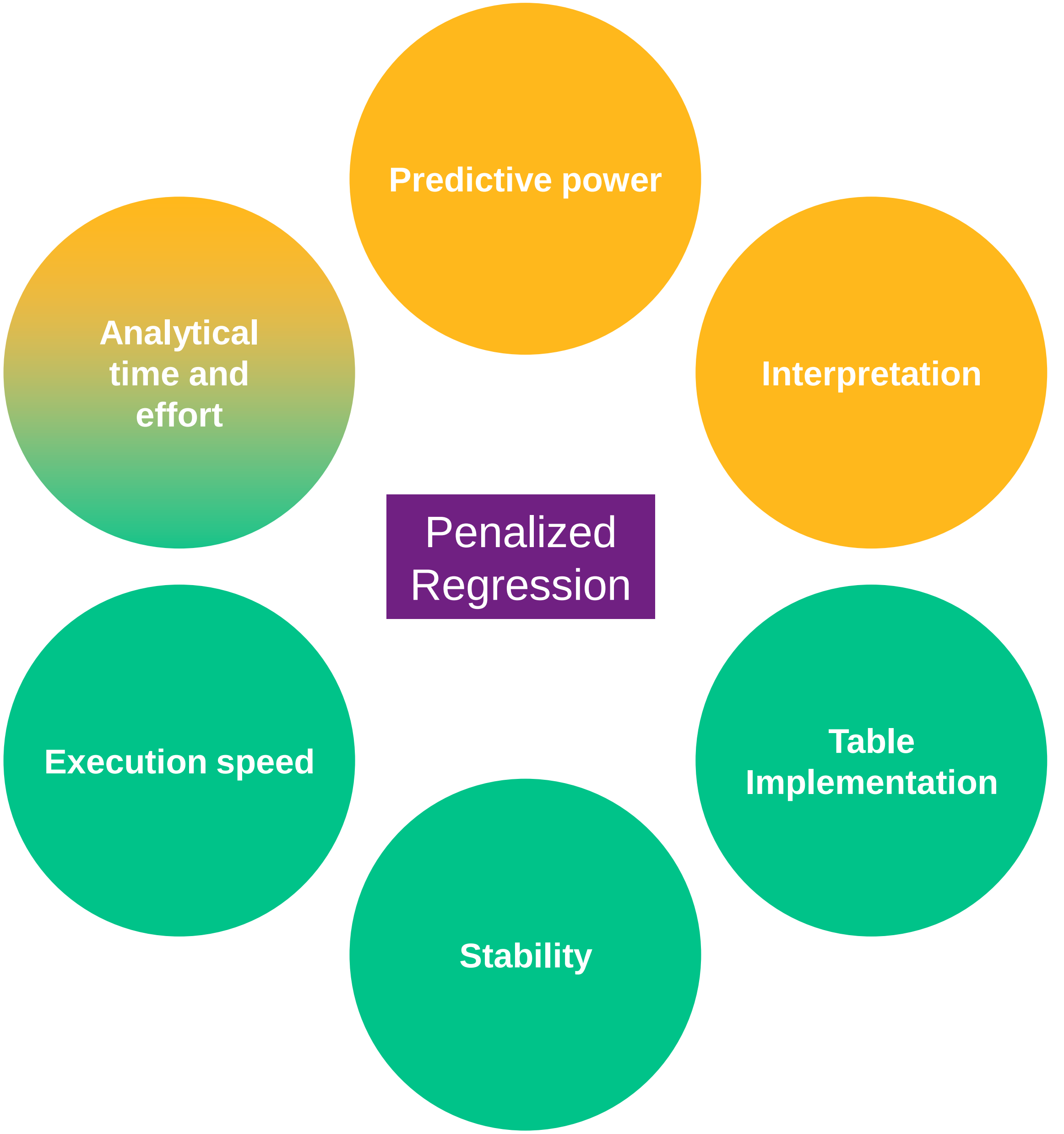
Deploying Penalized Regression

Same as GLMs!

	Age	Exposure	Loss Cost
1	<=20	1,720	179
2	21-30	34,893	122
3	31-50	118,182	102
4	51+	127,054	70
5	Age Total	281,849	91

	Vehicle Group	Exposure	Loss Cost
1	1-10	164,107	77
2	11-14	84,859	101
3	15-18	28,952	116
4	19-20	3,931	272
5	VG Total	281,849	91

	Gender	Exposure	Loss Cost
1	Male	197,339	92
2	Female	84,510	87
3	Gender Total	281,849	91

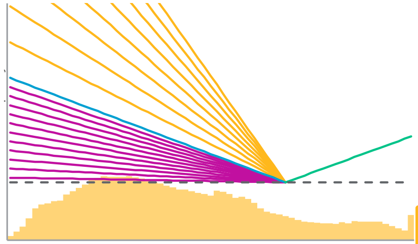

Predictive power
Analytical time and effort
Interpretation
Penalized Regression
Execution speed
Table Implementation
Stability

Practical applications of regression methods in pricing

Streamlining factor selection

Vehicle clustering

Geodemographic information



$$L(\beta|X,y) + \boxed{\lambda_1 \sum_i |\beta_i|} + \boxed{\lambda_2 \sum_i \beta_i^2}$$

GLM

Lasso

Ridge

Elastic Net

	Age	Exposure	Burning Cost
1	<=20	1,720	179
2	21-30	34,893	122
3	31-50	118,182	102
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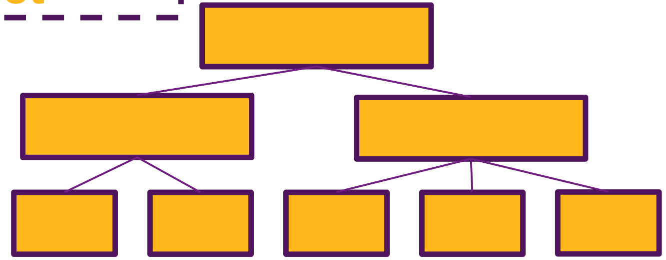


Simplification of ML models to improve interpretability

Modelling hierarchies

Some machine learning methods

Ensembles

Classifications Trees

"Earth"

Regression Trees

Gradient Boosting Machines

K-nearest Neighbors

Elastic Net

Neural Networks

Naïve Bayes

Random Forests

K-Means Clustering

Principal Components Analysis

Lasso

Support Vector Machines

Ridge Regression

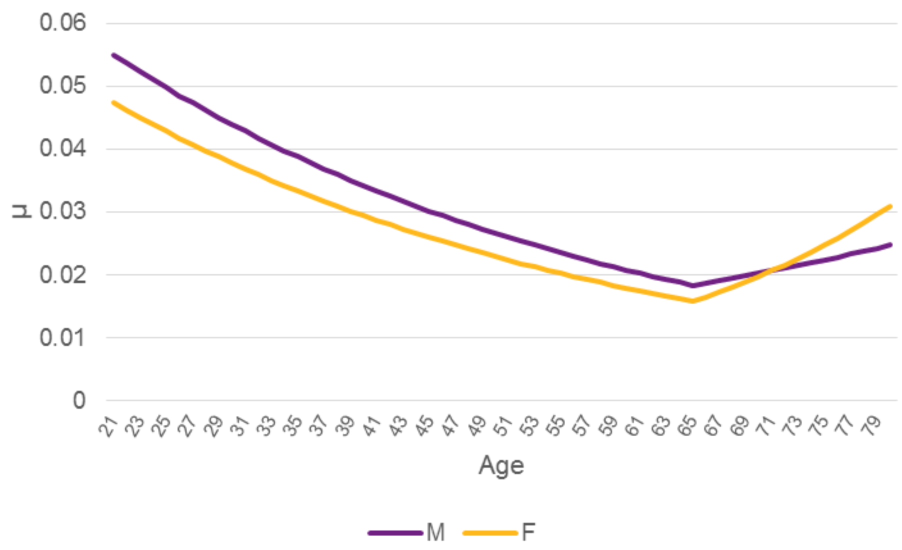
Focus on Neural Networks

Neural Networks

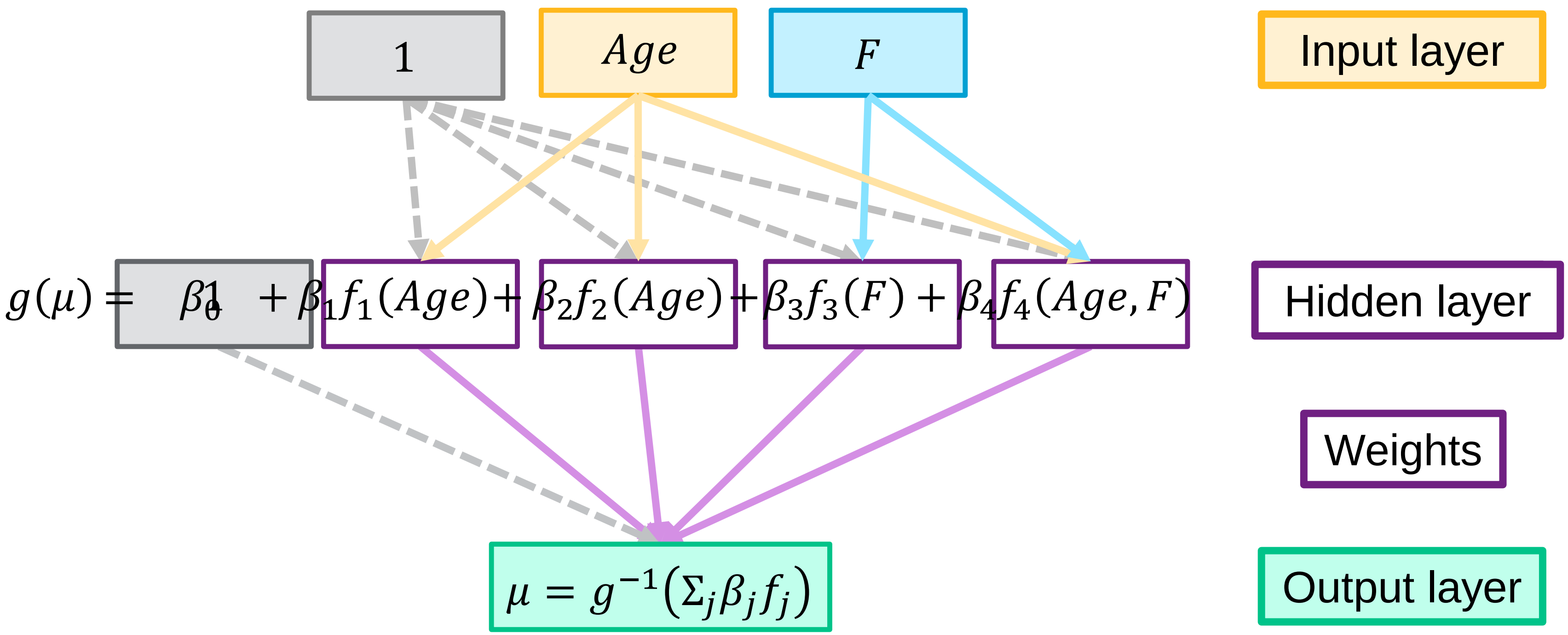
Start with a simple GLM…

- Log link function, g
- Age (piecewise-linear variates)
- F (indicator of Gender = Female)
- Age x Gender interaction

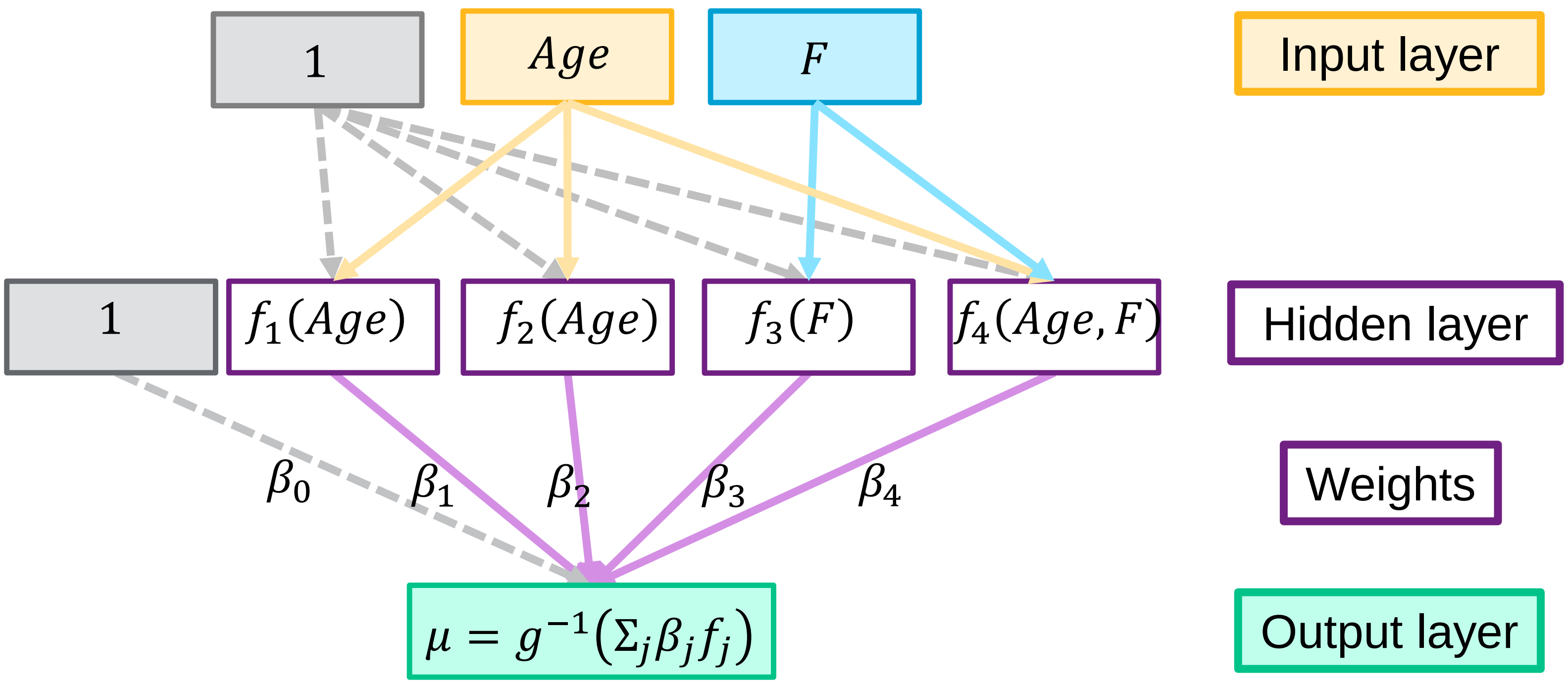
$$g(\mu) = \beta_0 + \beta_1 f_1(Age) + \beta_2 f_2(Age) + \beta_3 f_3(F) + \beta_4 f_4(Age, F)$$



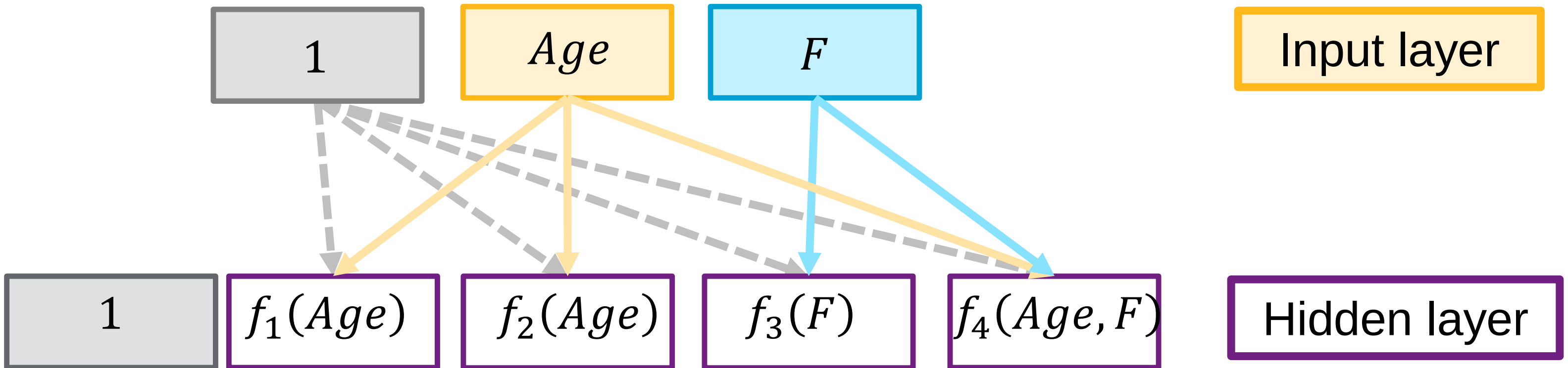
We can represent GLMs as a network…



We can represent GLMs as a network…



We can represent GLMs as a network…



Hidden layer represents our manually engineered features:

- $f_0 = 1$
- $f_1 = \max(65 - Age, 0)$
- $f_2 = \max(Age - 65, 0)$
- $f_3 = F$
- $f_4 = \max(Age - 65 - 100(1 - F), 0)$

General form:

- $f_i = \mathrm{ReLU}(w_{i,0} + w_{i,1} Age + w_{i,2} F)$

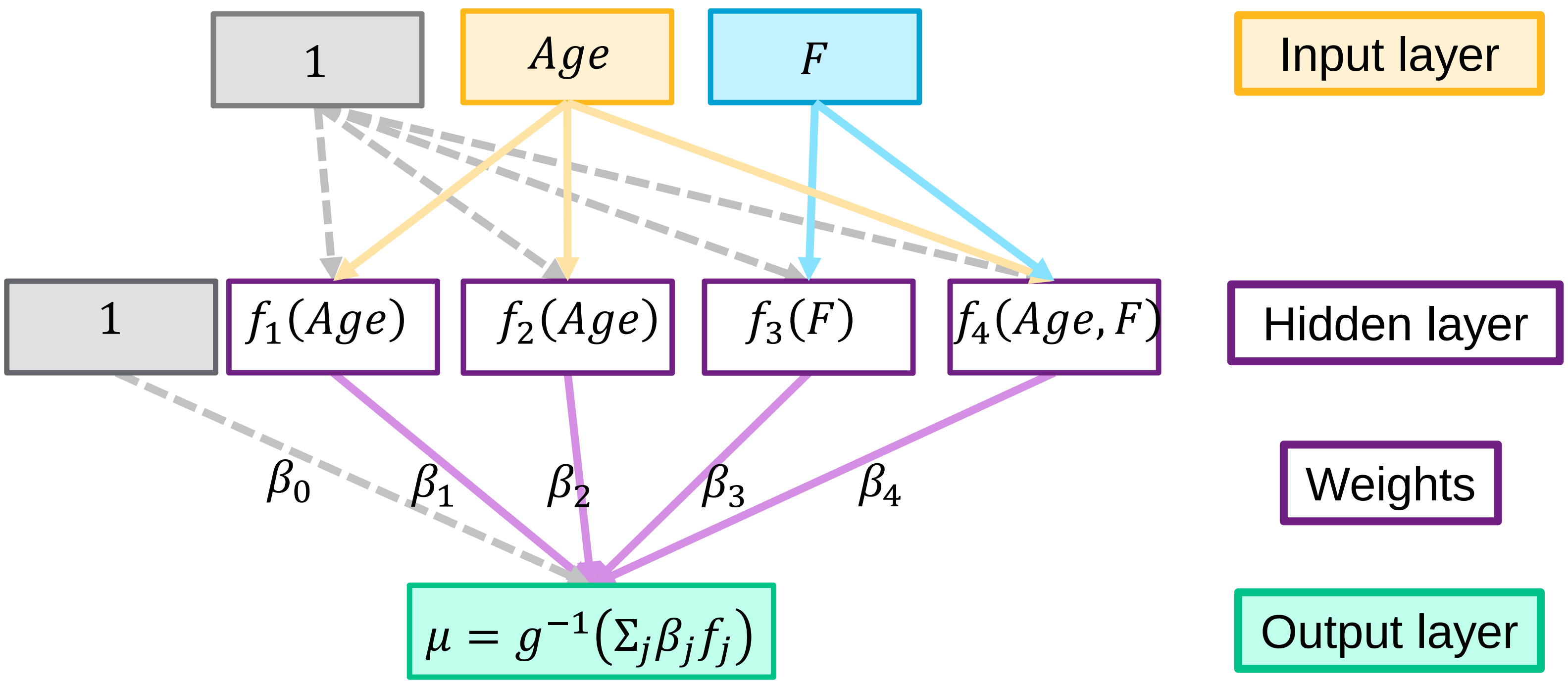
Activation function breaks linearity:

$$\mathrm{ReLU}(x) = \max(x, 0)$$

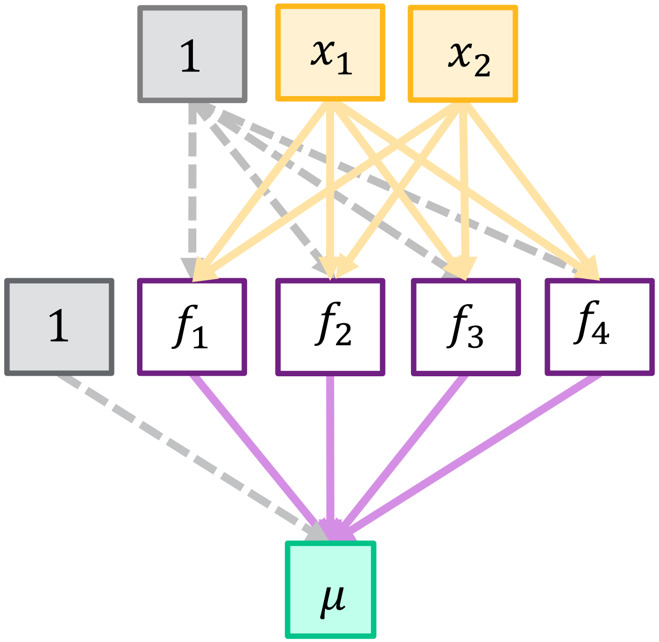
*(***Re**ctified **L**inear **U**nit)*

Universal approximation theorem:
We can approximate (almost*) any function arbitrarily well with a single hidden layer
*(*continuous, on compact subsets)*

We can represent GLMs as a network…



Generalizing to neural networks



Input layer (L0): x_i

Weights: w_{ij}

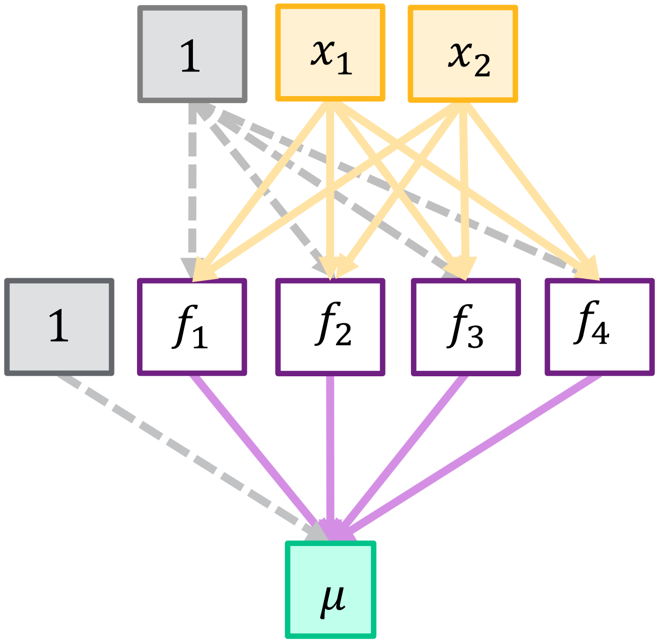
Hidden layer (L1): $f_j = h_1\left(\Sigma_i w_{ij} x_i\right)$

Weights: β_j

Output layer (L2): $\mu = h_2\left(\Sigma_j \beta_j f_j\right)$

Generalizing to neural networks

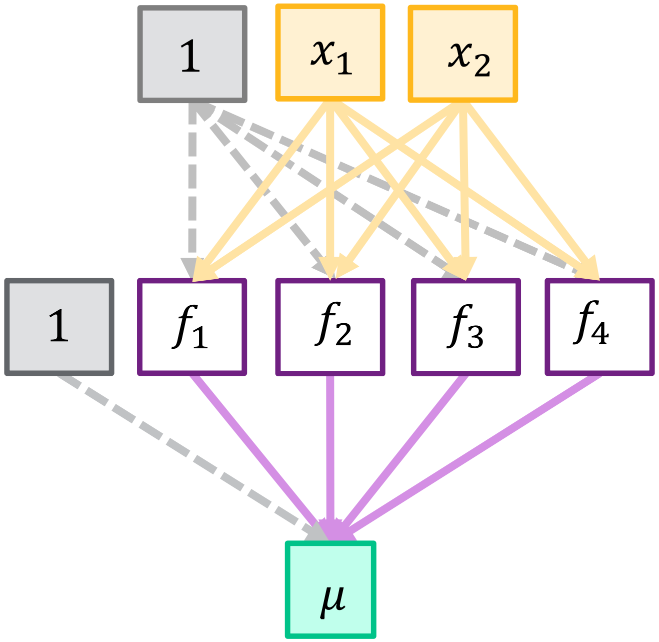
Model structure decisions



- Input features
- Number of hidden layers
- Size of each hidden layer
- Activation functions
  - Typically specified by layer
  - ReLU is most commonly used
- Connectivity of layers and weight sharing
  - Typically **fully connected** with **unique weights**
  - Many variants exist, eg: **Convolutional Neural Networks** for image classification connect nearby blocks of pixels and apply the same shared weights across each block

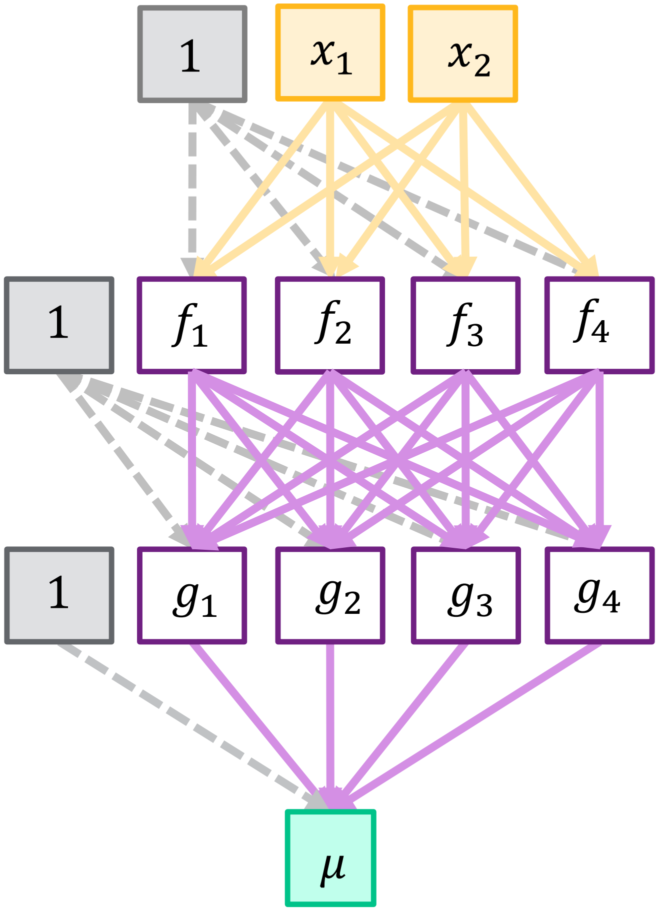
Generalizing to neural networks

Key model fitting decisions



- **Optimization algorithm**
  - Typically variants of **Back-Propagation**
- **Loss function** – to be minimized
- **Batch size** – number of rows to consider in each iteration
- **Epochs** – number of passes through full data
- **Initial weights**
- **Regularization parameters**, eg:
  - L1 / L2 penalties
  - Learning rate and decay
  - Dropout

Generalizing to neural networks



Input layer (L0): x_i

Weights: w_{ij}

Hidden layer (L1): $f_j = h_1\left(\Sigma_i w_{ij} x_i\right)$

Weights: v_{jk}

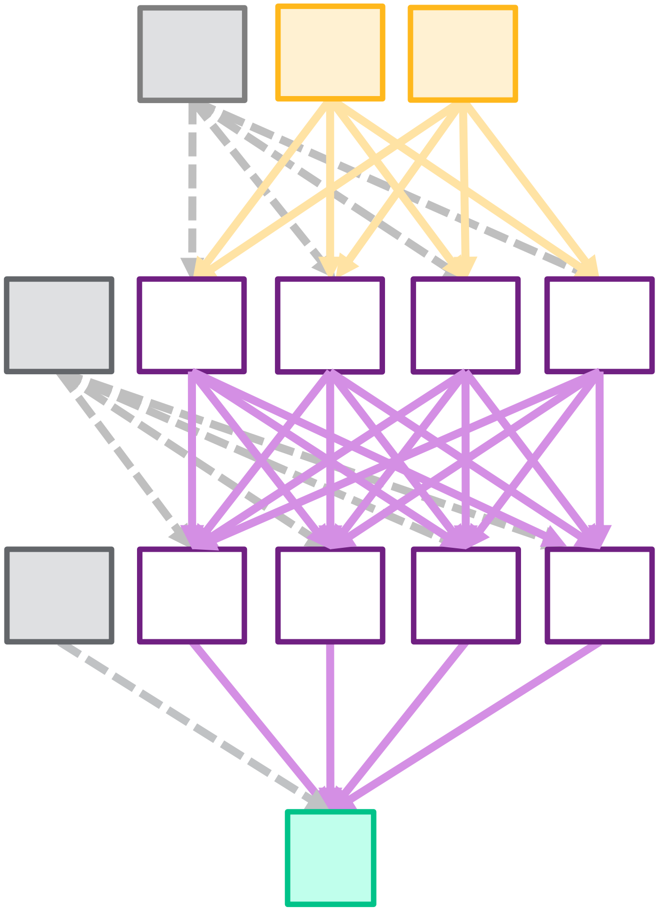
Hidden layer (L2): $g_k = h_2\left(\Sigma_j v_{jk} f_j\right)$

Weights: β_k

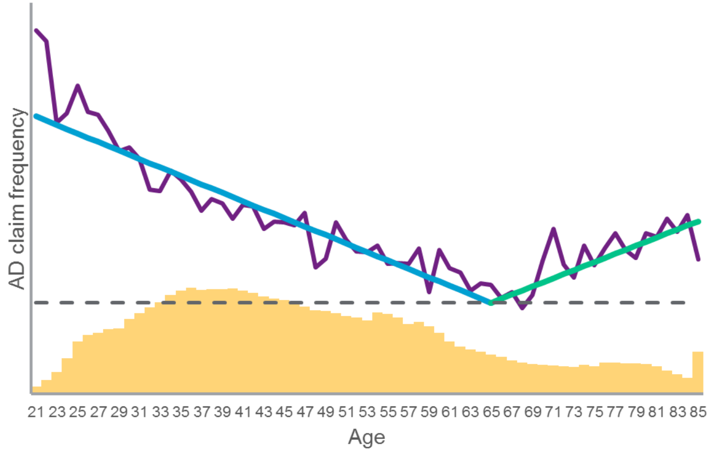
Output layer (L3): $\mu = h_3(\Sigma_k \beta_k g_k)$

"Deep learning" refers to multiple hidden layers

Generalizing to neural networks

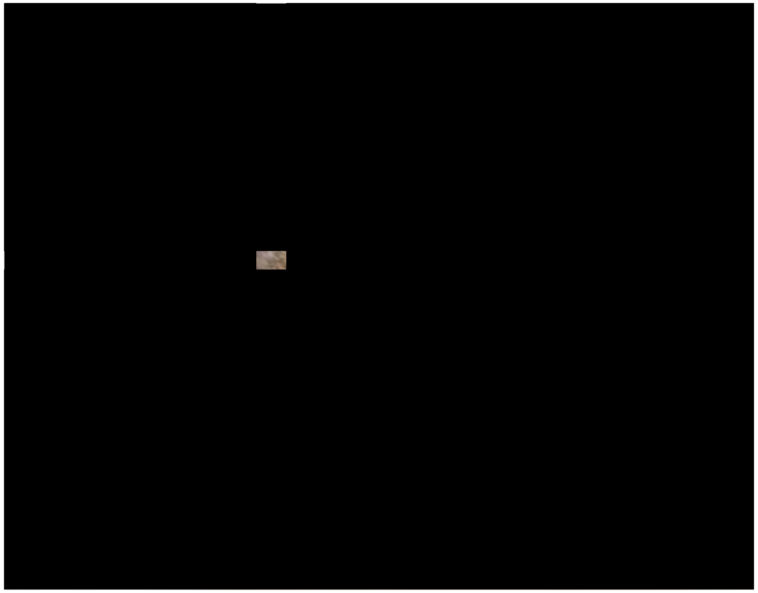


Where is the value?

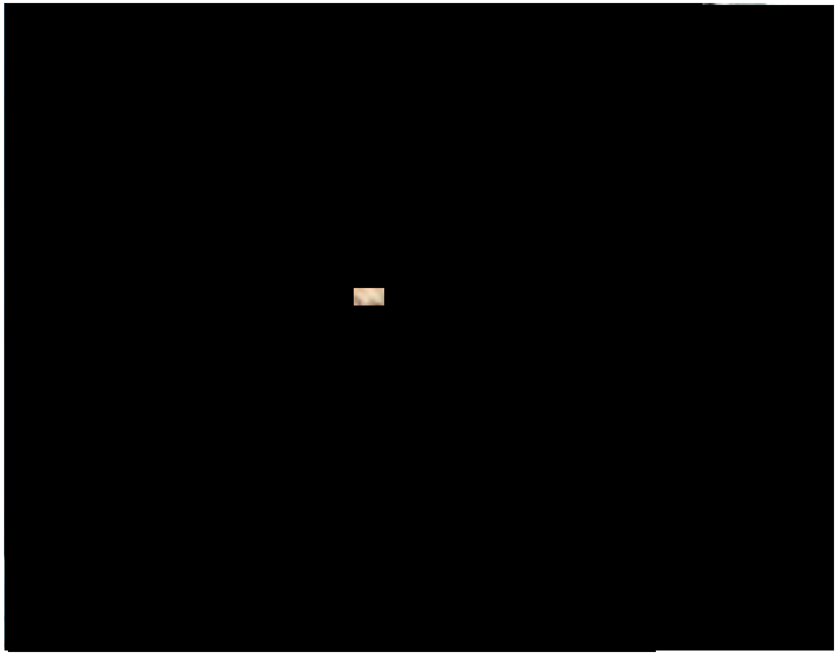


Which policyholder is more likely to make a claim?

Where is the value?



Which picture is more likely to be of a cat?

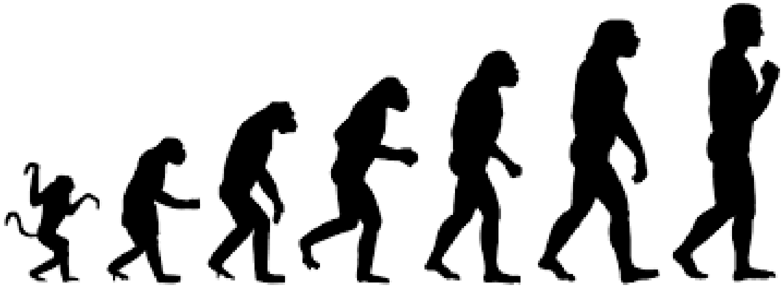


Where is the value?

Which picture is more likely to be of a cat?

Neural networks

Evolution or revolution?



Neural networks

Case study – market models

Context

- UK aggregator sites provide some historic quote data
- We wanted a model of "Average top 5 premium" for auto quotes to understand the market's pricing structure
- One month of data (~1m quotes)
- Limited subset of factors (no data enrichment beyond simple rating area & vehicle group)

Approach

- 60/40 split for training and holdout data
- Modelled as Log-Normal (ie $\ln(\text{Premium}) \sim N(\mu, \sigma^2)$) as Normal distributions well supported across packages
- Compare Neural Network performance to GLM (using existing model parameterizations) and GBM with RMSE of log-Premium on holdout data

Neural networks

Case study – GLM benchmark

Model	Test error	Training error
GLM	34.7%	34.0%

Neural networks

Require some work!

Dropout

Optimization algorithm

Input layer

Hidden layers

Output layer

Epochs

Learning rate

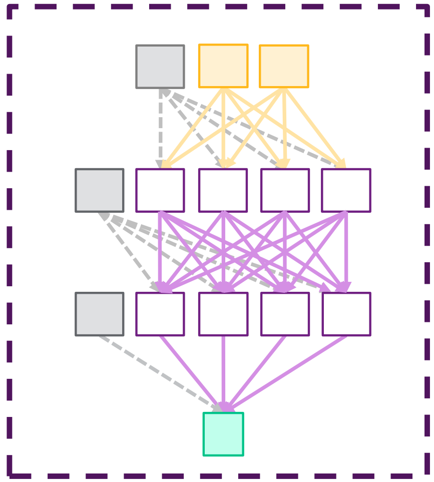
Batch size

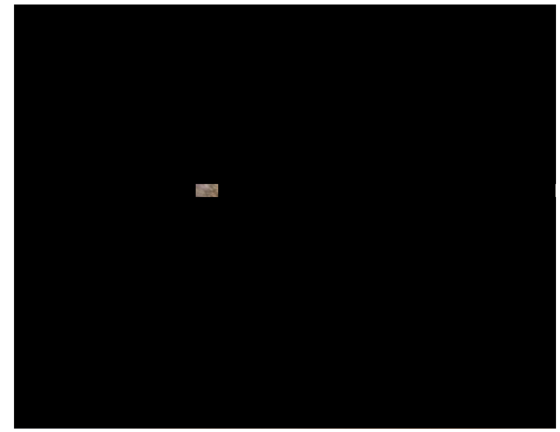
Regularization

Initial weights

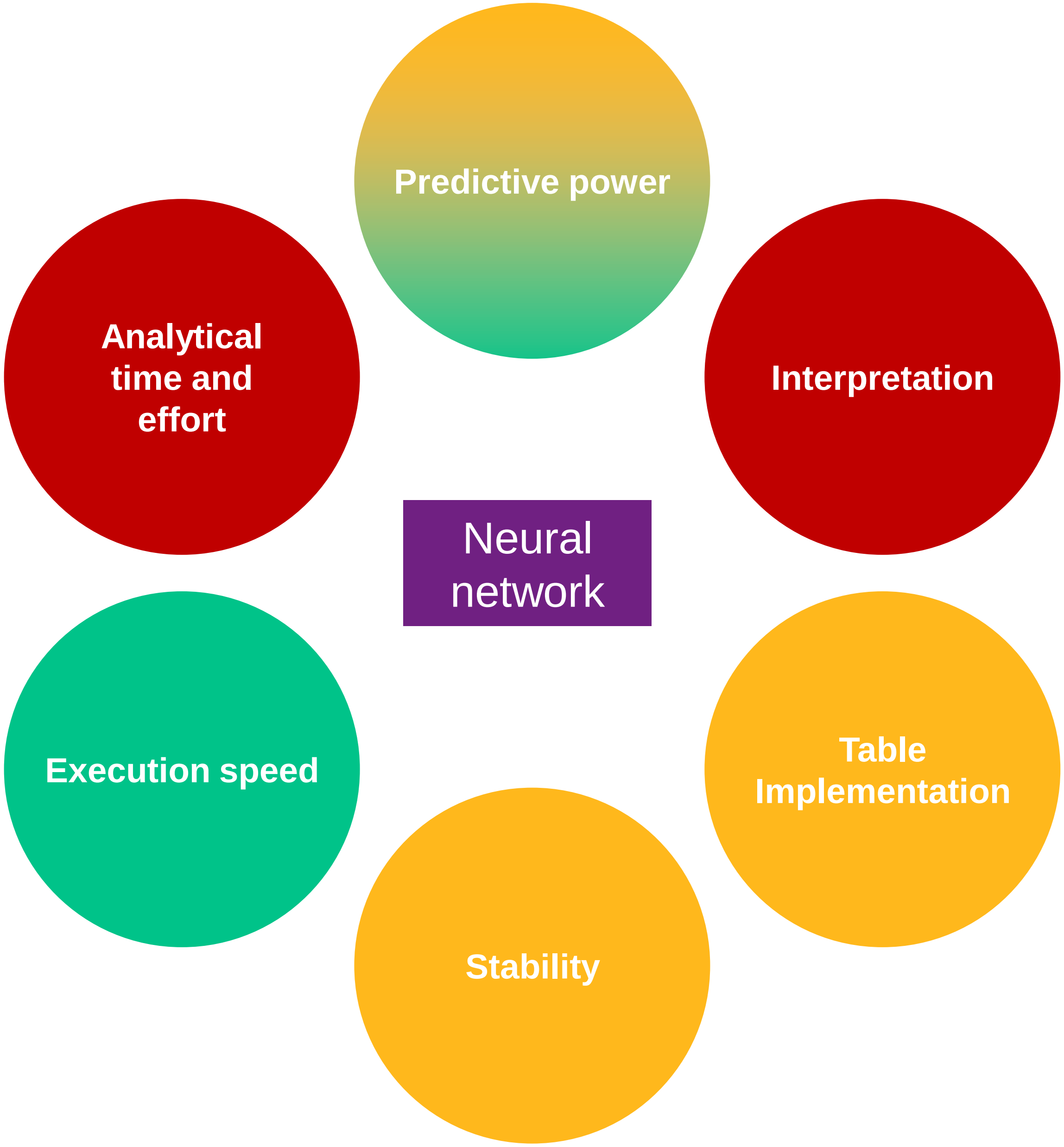
Activation functions

Practical applications of neural networks in pricing

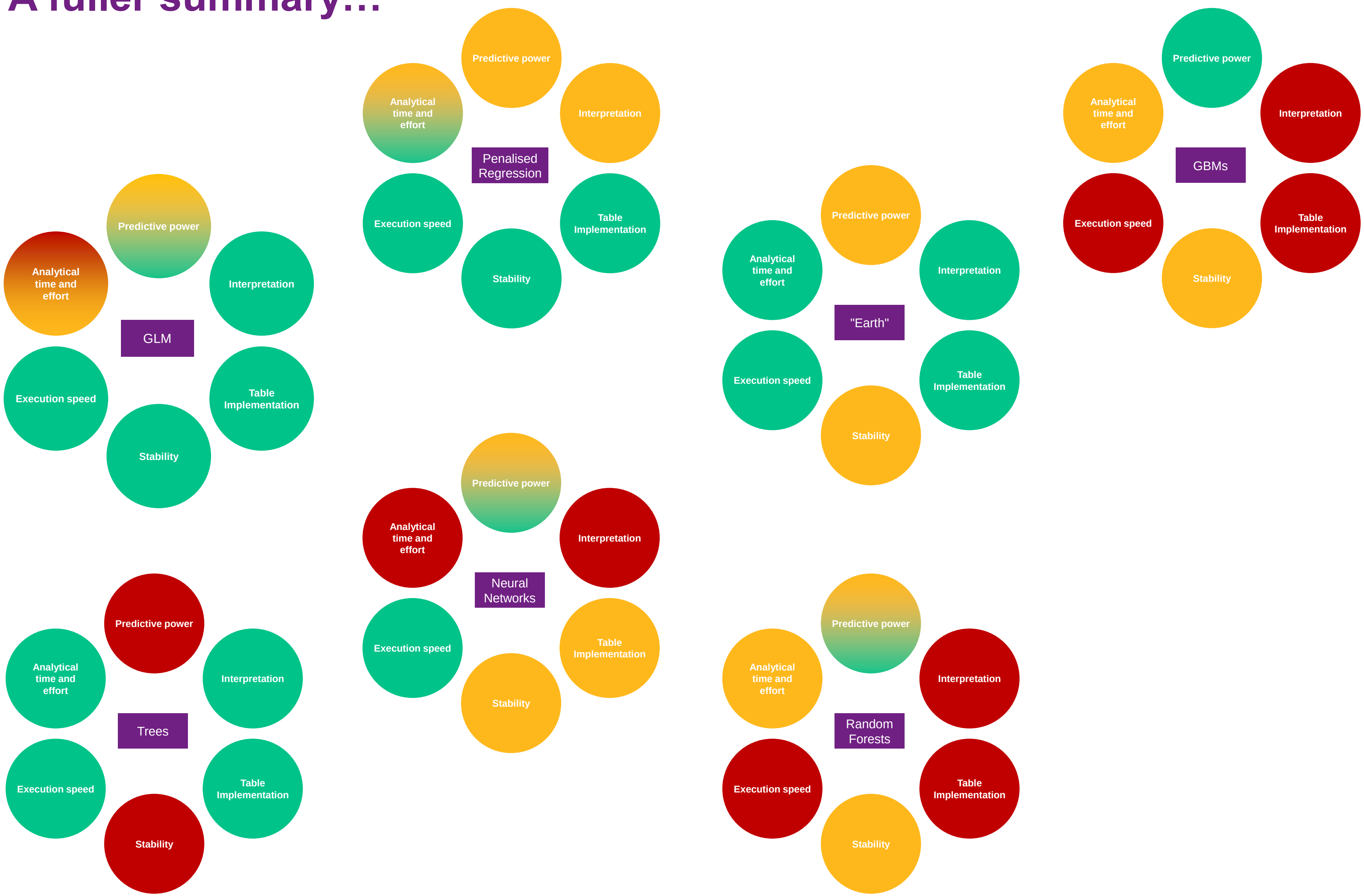




Marketing and Distribution → Customer management → Underwriting and risk management → Pricing → Claims management → Asset management

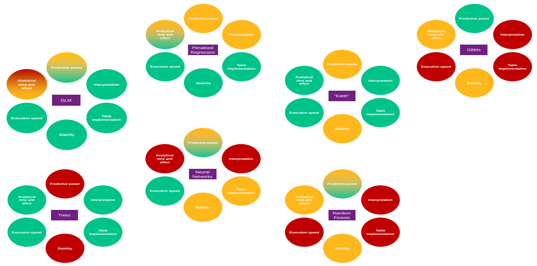

Predictive power
Analytical time and effort
Interpretation
Neural network
Execution speed
Table Implementation
Stability

A fuller summary…



Machine learning in pricing

Conclusions (Part 2)



- Machine learning brings a proliferation of new methods
- Improving models is more than just finding the best method. Consider:
  - What data are available and how can data be transformed to give insight
  - What is the optimal model structure and target variable?
  - How can information be transferred between models?

- Earth is a fast, interpretable method that can improve overall lift by informing when/where to segment models
- Neural networks are complex and require numerous input decisions; analyzing unstructured data (e.g., imagery) is an intuitive application for this method … but where else may it be helpful?
- Penalized regression can aid in factor selection decisions and may in fact be a good method in its own right – particularly when the modeler has less of a "feel" for the data

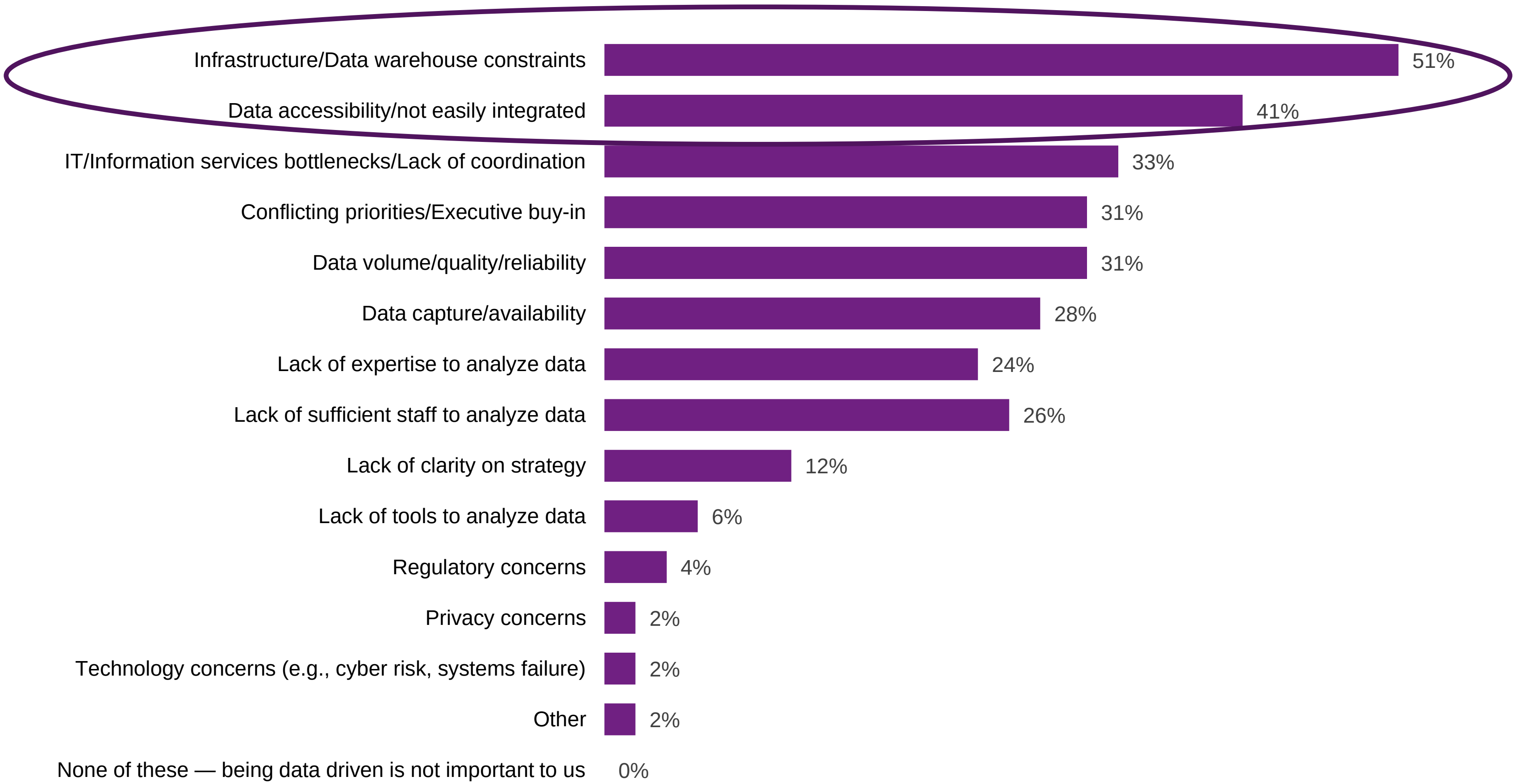
- Machine learning in pricing is not all about improving predictive power. Consider:
  - Fast investigation of new data
  - Quick assessment and response of emerging experience

So what? How is the US market doing with machine learning

Some critical success factors

Component	Rating	Directional trend
Data availability		Static
Appetite to try new approaches		
Modelling tools and platforms		
Internal skills sets		
Measuring value		
Application		

What are the three biggest challenges preventing your company from becoming more data driven? (Q.21)



Base: U.S. respondents (n = 51)

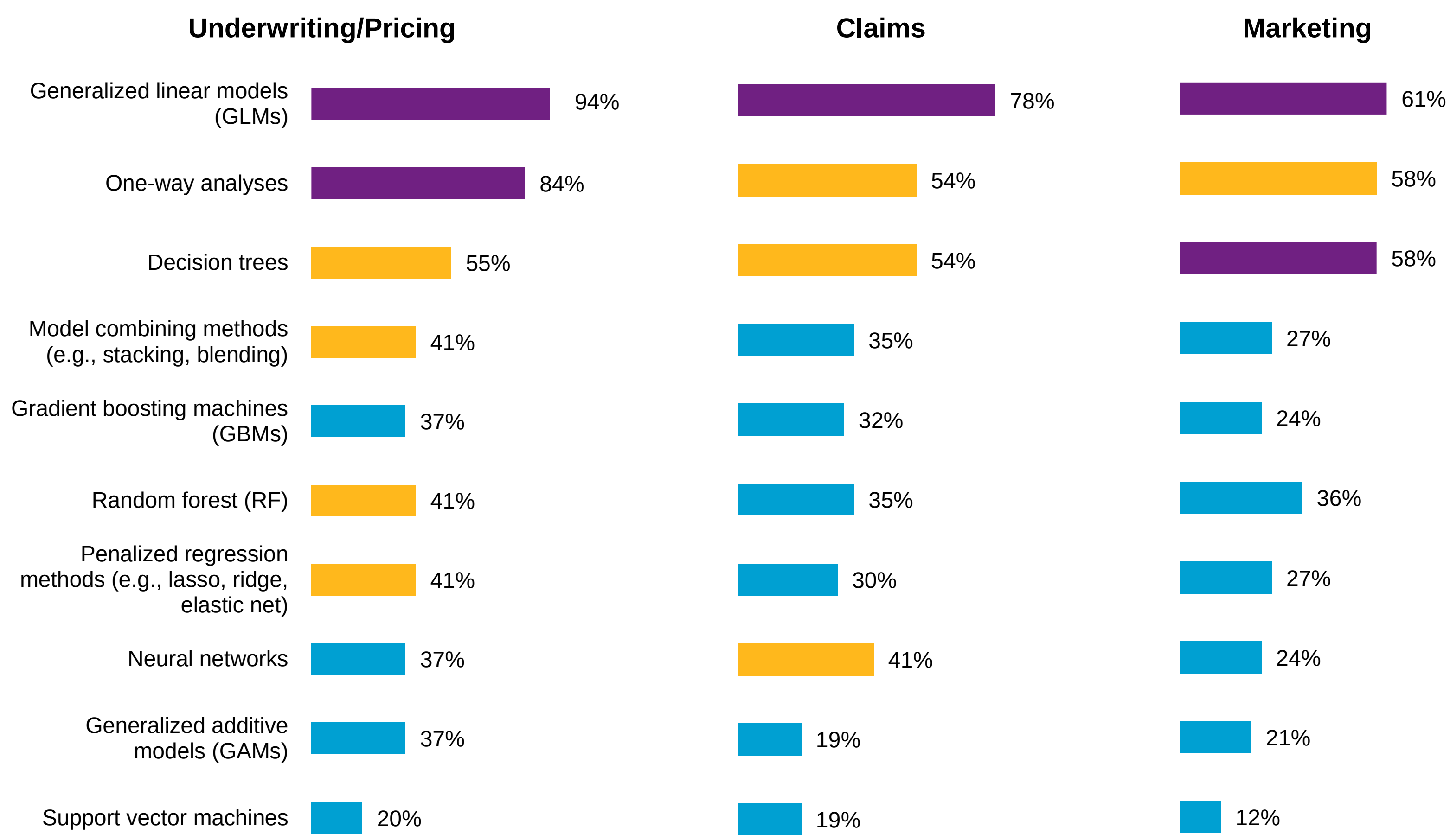
So what? How is the US market doing with machine learning

Some critical success factors

Component	Rating	Directional trend
Data availability		Static
Appetite to try new methods		Slowly upward
Modeling tools and platforms		
Internal skills sets		
Measuring value		
Application		

So what? How is the US market doing with machine learning

Methods used

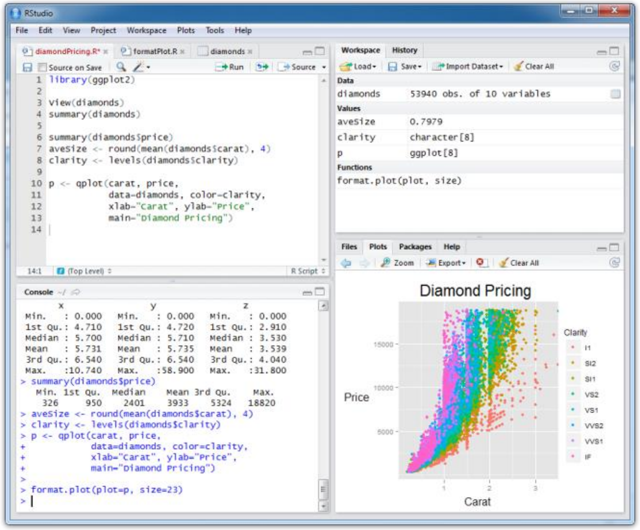


Base: U.S. respondents using advanced analytics for underwriting/pricing (n = 49), claims (n = 37) and/or marketing (n = 33)

So what? How is the US market doing with machine learning

Some critical success factors

Component	Rating	Directional trend
Data availability		Static
Appetite to try new approaches		
Modeling tools and platforms		Slowly upward
Internal skills sets		
Measuring value		
Application		



Cloud-based environments and Hadoop

Regardless of size, insurers are actively exploring technology to manage big data

	Large		Medium		Small	
	Now	Exploring	Now	Exploring	Now	Exploring
Cloud-based (Amazon Web Services, Azure)	**19%**	**48%**	**7%**	**50%**	**0%**	**40%**
Hadoop	**19%**	**37%**	**7%**	**14%**	**0%**	**20%**

So what? How is the US market doing with machine learning

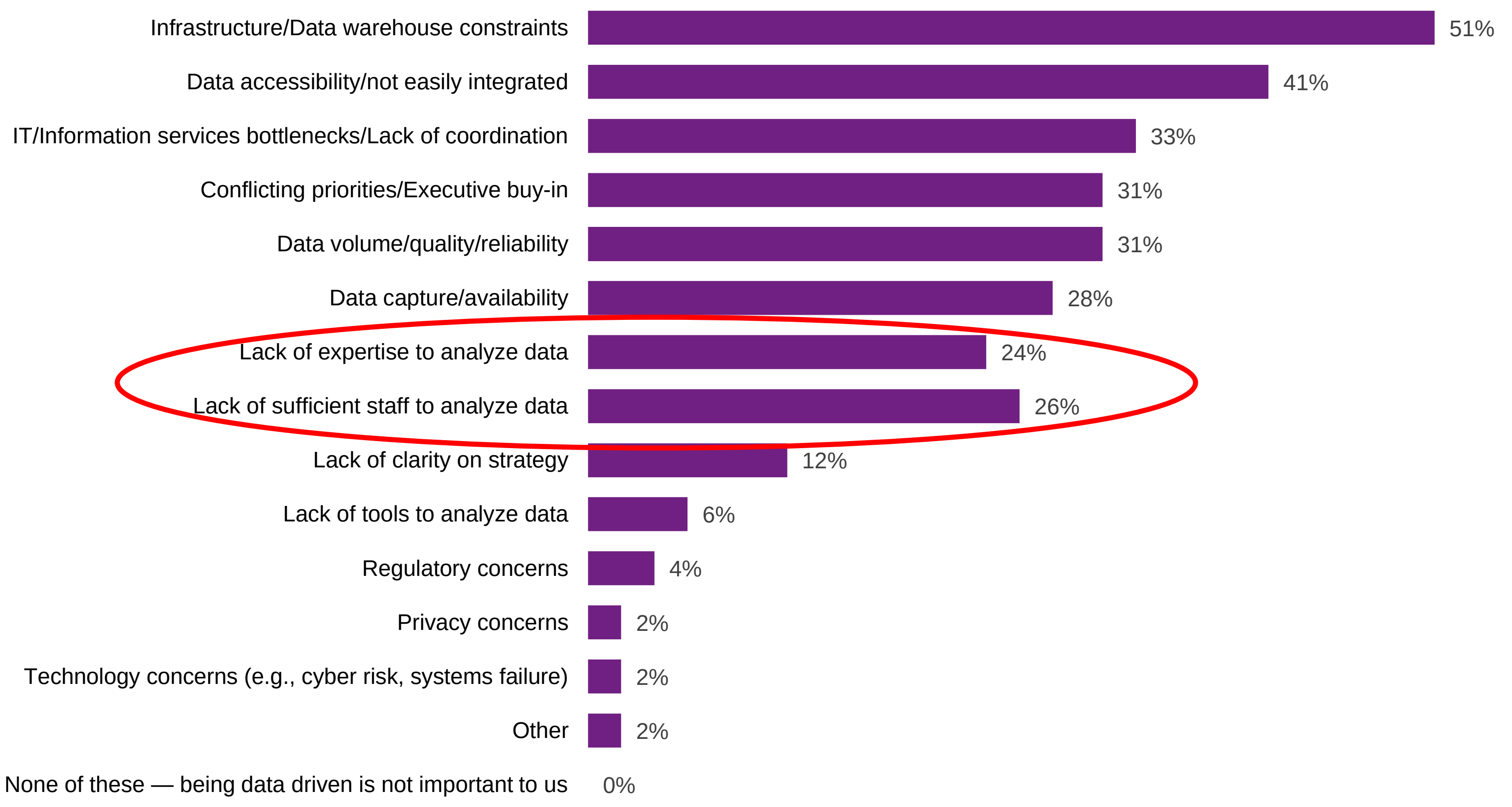
Some critical success factors

Component	Rating	Directional trend
Data availability		Static
Appetite to try new approaches		
Modeling tools and platforms		
Internal skill sets	?	Slowly upward
Measuring value		
Application		

"We're also seeing an influx of quantitative talent to the insurance industry. In addition to actuaries, insurers are hiring statisticians, data scientists, marketing scientists and behavioral scientists. The industry is challenging these professionals to solve a wider range of problems across the customer value chain"

- Recent article by Claudine Modlin and Graham Wright

What are the three biggest challenges preventing your company from becoming more data driven? (Q.21)



Base: U.S. respondents (n = 51)

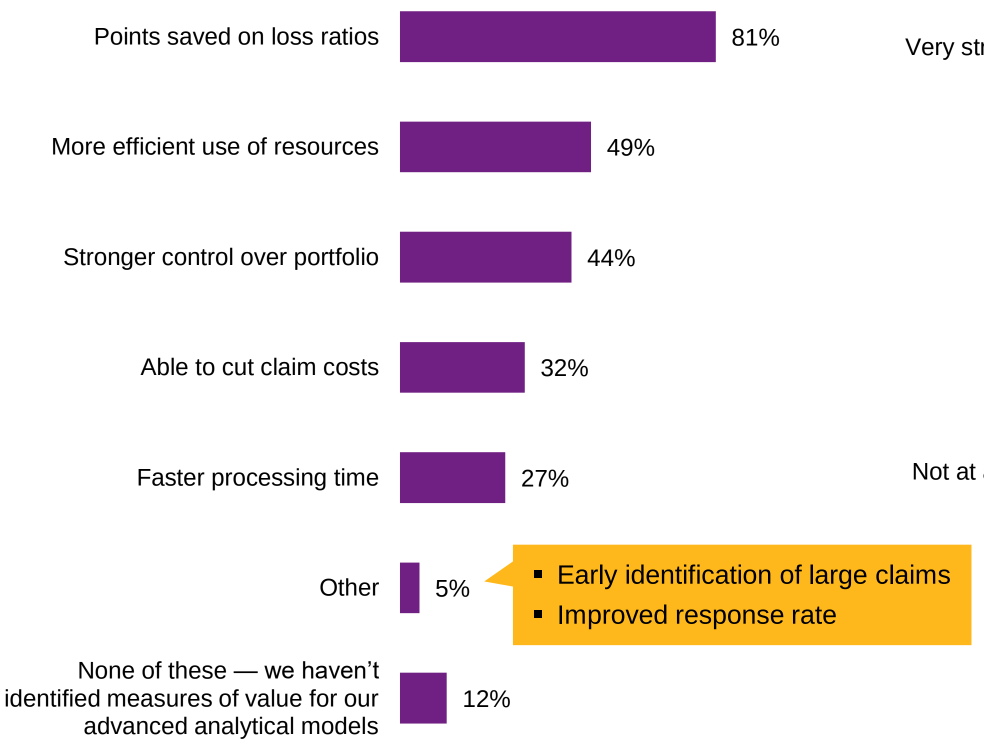
So what? How is the US market doing with machine learning

Some critical success factors

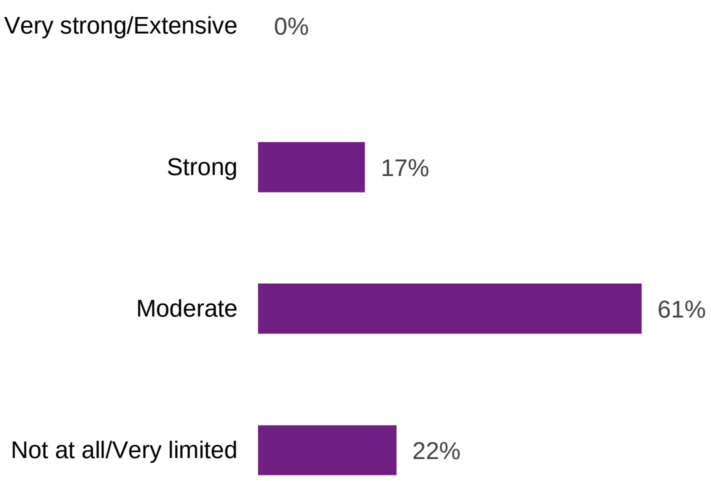
Component	Rating	Directional trend
Data availability		Static
Appetite to try new approaches		
Modelling tools and platforms		
Internal skills sets		
Measuring value		Static
Application		

How do you determine the value of your advanced analytic models? (Q.11) How well understood are your advanced analytic models by those who need to use them, outside of the modeling team? (Q.12)

Measures used to determine value of advanced analytics models



Level of understanding of advanced analytics models outside of the modeling team



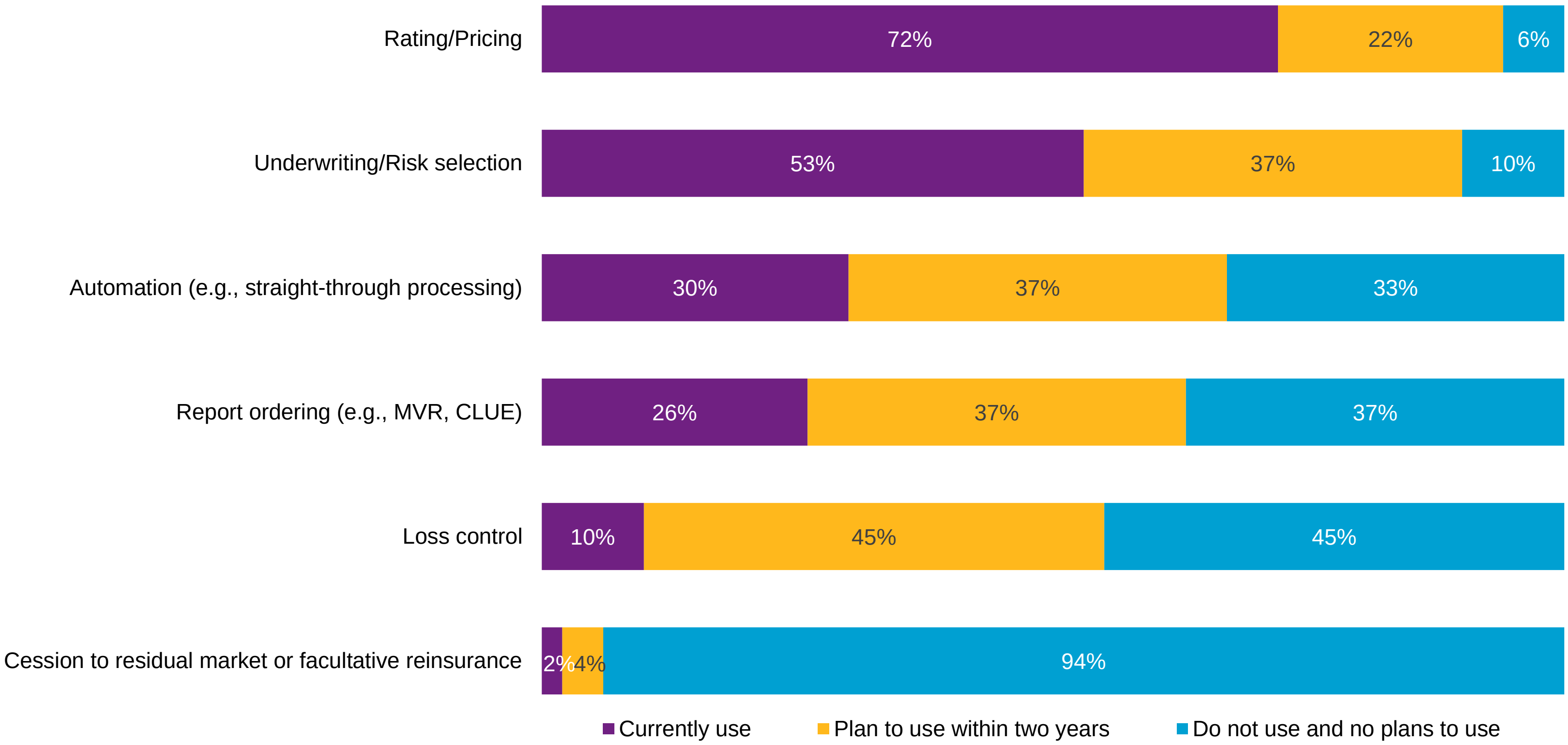
Base: U.S. respondents using advanced analytics to evaluate fraud potential (n = 41)

So what? How is the US market doing with machine learning

Some critical success factors

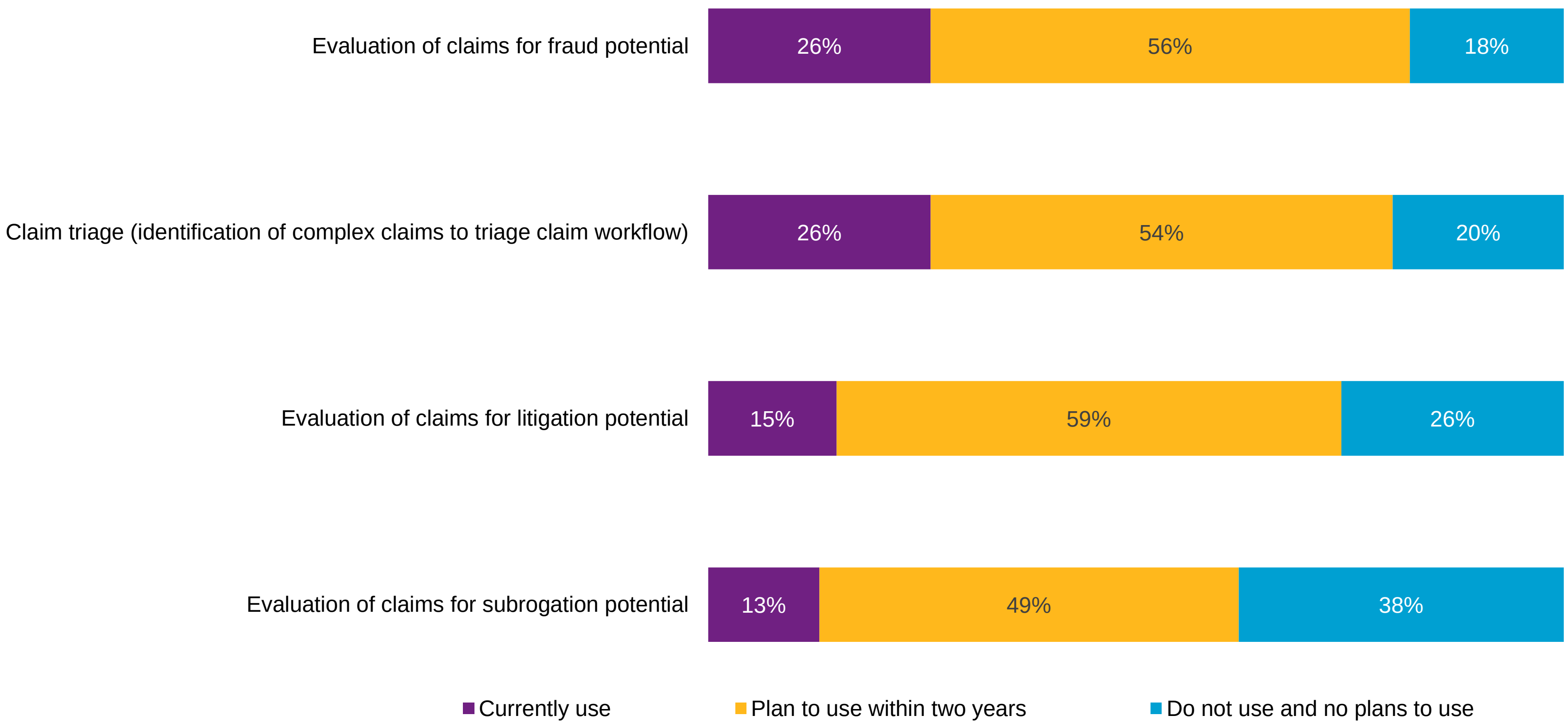
Component	Rating	Directional trend
Data availability		Static
Appetite to try new approaches		
Modelling tools and platforms		
Internal skills sets		
Measuring value		Slowly upward
Application	?	Slowly upward

For which aspects of underwriting/pricing does your company group currently use or plan to use advanced analytics? (Q.2)



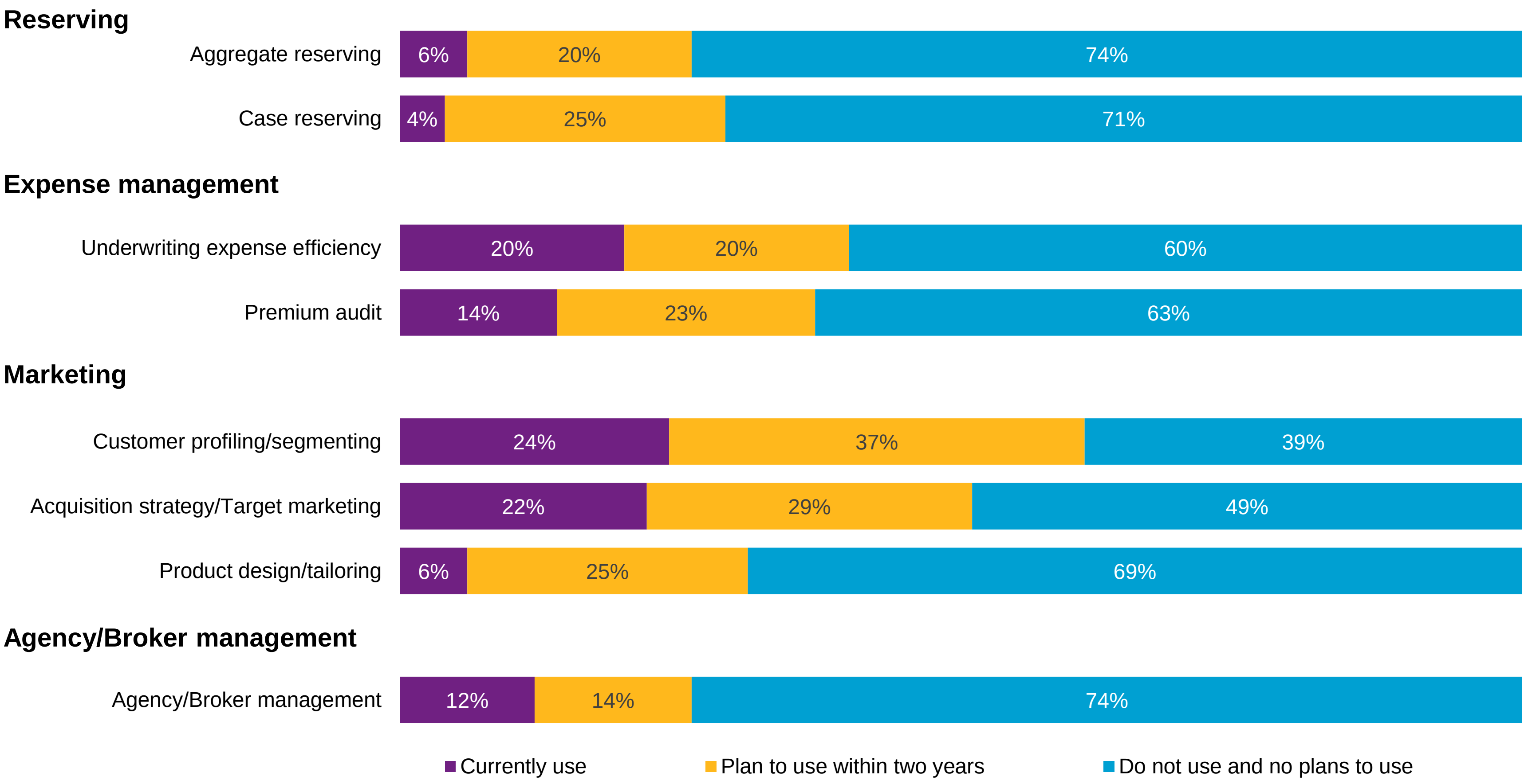
Base: U.S. respondents using or planning to use advanced analytics for underwriting/pricing (n = 51)

For which aspects of claims does your company group currently use or plan to use advanced analytics? (Q.4)



Base: U.S. respondents using or planning to use advanced analytics for claims (n = 39)

Beyond underwriting/pricing and claims, in which other areas does your company group currently use, or plan to use, advanced analytics? (Q.9)



Base: Total U.S. respondents (n = 51)

Machine learning beyond pricing

- Carriers are experimenting with ML, it is becoming established within insurance analytics
- It opens up a broader set of problems to analytics, and offers a broader tool set for familiar problems
- New (wider) data beats new methods – think UBI!
- Factor definition, problem specification and method selection are critical for success
- There's opportunity to reveal actionable, first-order insights in applications to which analytics have not been deployed previously
- With this broad new opportunity, spotting strong initial use cases is important

Questions

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